Wage Setting over the Business Cycle and the Effect of Employment Protection on Human Capital Formation

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Contents

List of Figures

List of Tables

Introduction

Labor is - and always has been - the principal factor of production. In a modern industrialized economy, about two thirds of income accrue to labor. Therefore, in order to understand the functioning of an economy, it is essential to fully grasp the mechanisms that steer the use of this factor. As the carrier of human capital, labor is important for the explanation of economic growth. As to the short run, movements in the labor market are central to the understanding of the business cycle, as Kydland (1995) points out: "most business cycle theorists agree that an understanding of labor market fluctuations is a prerequisite for understanding how business cycles propagate over time."

Labor is not only a factor of production. It is also a central element of human existence: people derive satisfaction from working. Those who are excluded from the active labor force are deprived of a fundamental element of their human condition. Therefore Layard, Nickell and Jackman dedicate their (1991) book "to the millions who suffer through want of work". Unemployment is a waste of resources and comes at a high cost for society and for those individuals who experience it. Unemployment has often been the origin of agitation and discontent. In economic policy, the fight against unemployment has always been one of the most predominant issues. Economists try to understand the mechanisms of the labor market and figure out how labor market policy can be performed, and how institutions can be designed in order to avoid unemployment.

This dissertation is about labor market institutions and the implications these have on allocative outcomes. The first chapter studies the effect of the business cycle on the setting of entry-wages, i.e. wages that people get at the start of a new job. I estimate the elasticity of entry wages with respect to aggregate productivity, using data from the Current Population Survey of the United States. The entry wage is particularly important as it behaves proportionately to the present discounted value of the expected sum of total wage payments that the worker will receive in the life time of the job. Therefore, entry wages are allocative and influence the extent of vacancy creation. I find that entry wages react strongly to fluctuations in aggregate productivity. This has important consequences for flow models of the labor market. The second and the third chapter take a closer look at a specific labor market institution: employment protection (EP). It is often argued that firms will invest more in their employees' human capital if they cannot lay them off easily when the situation worsens. In the second chapter, I examine this hypothesis using a model of human capital accumulation and the labor market. I calibrate the model to an economy without employment protection and use numerical methods to study the effects of the introduction of a firing tax and severance payments. I find that a moderate firing tax indeed has a positive impact on the firms' incentives to organize on-the-job training for their employees, but at the cost of reducing firms' profits. The third chapter provides some empirical evidence on the interrelations between employment protection and on-the-job training in Germany. I use date from the Qualification-and-Career Survey and apply the method of difference-in-differences. I find evidence that corroborates the theoretical results from the second chapter.

In the remainder of this introduction I outline some basic concepts that are used throughout this dissertation. I describe the fundamental mechanisms in the labor matching model and discuss some of its implications. Then, I trace out the concept of human capital. Summaries of the three chapters of this dissertation follow.

Basic Concepts

Modern labor market research is dominated by the paradigm of the search and matching model. It was developed in the 1970s and 80s especially by Diamond, Mortensen and Pissarides (see Diamond, 1982; Mortensen, 1970; Pissarides, 1979, 1984). A comprehensive exposition of the model that covers the standard form and many extensions is given by Pissarides (2000).[1] As the model is extremely versatile it is being used to analyze many types of questions that arise in the labor market.

The concept that underlies the model is that of *equilibrium unemployment*. Equilibrium unemployment is equivalent to the natural rate of unemployment that was coined by Friedman in his (1968) presidential address to the American Economic Association. Economists became increasingly convinced that monetary policy could influence unemployment (and other macroeconomic variables of interest) only in the short run. In the long run they should be determined by "real factors" i.e. quantities of goods and resources, technology, preferences and institutions and relative prices. The rate that actual unemployment converges to and that is determined by the real factors was named the "natural rate" or "equilibrium unemployment". Economists sought to develop a theory that abstracted from monetary policy that could explain this rate.

Layard, Nickell and Jackman (2005) give a (non-exhaustive) list of factors that influence equilibrium unemployment: The unemployment benefit system, active labor market policies, the real interest rate, employment protection laws, barriers to labor mobility, the

[1] The book contains also a summary of the evolution of this theory. The history of the matching function is summarized by Petrongolo and Pissarides (2001).

system of wage determination, product market competition and labor taxes.

The matching model has proven to be a very useful tool for labor market research as it captures better than other models many things that we observe in actual labor markets: Workers search for jobs and it takes time until they find suitable ones. The wages are bargained between the firms and the workers. Sometimes, workers become unemployed. The principal premise is the insight that the labor market is a market with frictions, demand and supply do not find their equilibrium instantaneously. It takes time and resources to match jobs to workers. Therefore, adjustment to equilibrium is costly. The frictions arise because jobs and workers are heterogeneous and information is incomplete on both sides of the market. Not every job searcher fits into every vacancy, and it takes time to sort out who is who and what is what. These frictions are introduced into the model in two forms: by the vacancy posting cost and by the matching function.

The matching function accounts for the fact that job searchers and vacancies coexist in the same market. It captures the frictions that impede immediate matching of all job searchers to vacancies. It maps the number of job searchers and the number of vacancies into the number of job matches created. The function thus describes a relationship between aggregates like an aggregate production function, or like the utility function of a representative individual. In the empirical literature, these frictions that the matching function accounts for are denominated as “mismatch”. “Mismatch is an empirical concept that measures the degree of heterogeneity in the labor market across a number of dimensions, usually restricted to skills, industrial sector and location” (Petrongolo and Pissarides, 2001). The industrial sector is relevant here because of industry specific skills that workers have. The fact that the number of job searchers does not coincide with the number of vacancies in a certain geographic area is called *imbalance*. Therefore, in a narrower sense mismatch refers to the discrepancy between skill requirements of vacancies and the workers’ skill endowments, and imbalance refers to the differences in location (see Petrongolo and Pissarides, 2001). The matching function is supposed to catch all these frictions in the labor market. One caveat of the matching approach is that there is not yet a widely accepted microfoundation for the matching function.[2]

The other component that introduces frictions into the matching model is the vacancy posting cost. Paying it, a firm obtains the right to search for exactly one worker. The distinctive feature of these costs is that *they are sunk as soon as the firm and the worker have found each other and begin to bargain over the wage.* After having started bargaining, the firm can exchange the worker only by again paying the vacancy cost and repeating the search process. Thus, the firm is locked into the relationship, the payoff from continuing with the match is higher than from the next best alternative. This gives rise to a holdup problem: The firm has invested in the relationship and the worker can threaten the firm to

[2] See Stevens (2007) for a microfoundation.

walk away leaving the firm with nothing. On the other hand, by dedicating time and effort to search, the worker has done some investment as well. She would also lose something if the firm laid her off. The matching surplus is the payoff from staying together minus the sum of the firm's and the worker's outside options. It is a quasi-rent about which the worker and the firm contend. Thus, the firm and worker find themselves in a bilateral monopoly. This type of problem has been analyzed in the economic theory of institutions in the late 70s (see Klein, Crawford and Alchian, 1978). Williamson (1986) called this change from an ex ante competitive setting to an ex post monopoly the "fundamental transformation". In the matching model this dilemma is typically solved by assuming that the firm and the worker share the surplus according to the *Nash bargaining solution*. Each gets a portion of the surplus that corresponds to her bargaining power.

These occurrences on the micro level have repercussions on macroeconomic equilibrium: When the workers eke out higher wages, the firms' profits are reduced, which lowers the incentives to create vacancies. Depressed vacancy creation reduces the searchers' prospects of finding jobs, and so the workers' outside options in the wage bargain. The zero-profit condition assures that vacancy creation and hence the workers' outside options are depressed to such an extent, that the firms' shares in the wage bargain are just enough to recover the outlays for vacancy creation. This is the mechanism that creates unemployment in the matching model. In a nutshell, unemployment serves as a device to keep the workers' wage demands in check. It can also be seen as a special case of an insider-outsider problem: It is the insiders who bargain the wage, but the wage affects vacancy creation and therefore the chances of the outsiders (the job-searchers) to find jobs. The insiders don't take this into account. Hosios (1990) has shown that this inefficiency is solved if the workers' bargaining power is equal to the elasticity of the matching function with respect to unemployment. This condition is unlikely to be fulfilled in reality, though.

Beginning with Merz (1995) the matching model has been used to analyze the behavior of labor markets over the business cycle. Recently, the quantitative implications of the model are the subject of an ongoing discussion. In an influential article, Shimer (2005) argues that the matching model cannot generate the cyclical fluctuations of the unemployment rate and vacancy creation that we observe US labor market data. The model generated volatility in these variables is far too low. Costain and Reiter (2008) come to a similar conclusion. The problem is that in the model the firms' incentives to create vacancies do not change much over the cycle. In the model, the cycle is expressed by changes in aggregate productivity. A rise in aggregate productivity translates immediately into higher wages, so that the worker gets the largest part of the increase in productivity and the firms' profits go up only a little. A small increase in profits leads to only a small increase in vacancy creation and consequently matching. Therefore, in response to a positive productivity shock the rise in vacancy creation and the reduction in unemployment are too small. In data the response is much larger. It appears that the matching-model which is currently used as a standard model of the labor market is inadequate to explain the cyclical pattern of its two most central elements: vacancies and unemployment. Shimer's and Costain and Reiter's contributions have entailed a debate about which is the best way to "fix" the model in order to make it match the facts.[3] Some have argued that assuming a type of wage rigidity could be the answer. If the wages are rigid and do not react instantly or not fully to the rise in productivity the firm can bag the production gains. Hall (2005) proposes such a model of wage rigidity. In his model, instead of Nash-bargaining the wage each period, the wage is constant and does not react to fluctuations in productivity as long as the firm does not run into negative profits - and the worker's outside option does not grow beyond her wage payments. If the firm's profits fall to zero or the worker's outside option rises too much, the wage is rebargained.[4] The following aspect is important: Wage rigidity is needed not only in existing matches but also in new job-matches. In Hall's model there is only one wage for all workers. This extends wage rigidity from existing job matches also to newly hired workers. Wage rigidity would not help if it were only present in existing job-matches but wages in new matches were given the Nash-bargained wage. This ongoing discussion is the motivation and prologue to the first chapter where I analyze the reaction of entry wages to changes in aggregate productivity.

Another theoretical concept that will be relevant in the second and third chapter is human capital. The concept of human capital was introduced into economics by Schultz in 1960: "I propose to treat education as an investment in man and treat its consequences as a form of capital. Since education becomes a part of the person receiving it, I shall refer to it as human capital." The use of the term "human capital" in this context was new. In the beginning, the new concept was not without controversy as can be seen from the following citation: "The mere thought of investment in human beings is offensive to some among us. Our values and beliefs inhibit us from looking upon human beings as capital goods, except in slavery and this we abhor" (Schultz, 1961). Schultz' interest in human capital was motivated by the huge unexplained part that arose in growth accounting. He saw that human capital was the key to understand many questions of economic growth. Nowadays, the macroeconomics of growth and development cannot be imagined without this concept.

The application of human capital proved also to be fruitful in the theory of income distribution. It was encouraged by the observation that the largest part of income inequality was due to the variance in labor incomes. The theory of income distribution was not very

[3]Cardullo (2008) surveys the debate and summarizes the different propositions.

[4]Hall also proposes other wage rules with moving wage. The central point is that the wage increase is smaller than the increase in productivity.

developed at that time. Prevailing ideas were that earnings differentials compensate the workers for the risk associated with different professions. Beyond, income inequality was seen as the consequence of different individual abilities, of (inherited) property or of sheer luck. Mincer (1958) was the first attempt that used human capital to explain income distribution. Another novel feature was the perception of education as an investment. So far, the predominant view was that education was a type of consumption. The theory of these issues was further developed and summarized by Becker (1964). He presents the knowledge of that time and subjects the theory to a comprehensive empirical assessment. He also introduces some important concepts, namely the distinction of specific and general human capital.

All these features will be important in the second and third chapters: Education is an investment, and income inequality will be determined by the stock of human capital that a person owns. Human capital is like an asset, but ownership cannot be transferred from one person to another. This makes it differ from physical capital. A discussion of the more recent developments in this theory is deferred to the second chapter.

The purpose of this section has been to present the origins of the ideas that are used throughout this dissertation and to give background information on the issues developed in the later chapters. A brief summary of the individual chapters and their main contributions is given in the following section.

Chapter Summaries

The first chapter **Wage Rigidity and Job Creation** studies the cyclical behavior of entry wages, i.e. those wages that workers receive after starting a new job. I argue that these wages react strongly to aggregate labor market conditions, in particular to changes in aggregate productivity. To show this, I estimate the elasticity of entry wages with respect to productivity.

The first contribution of this chapter is the construction of a time series of the aggregate entry wage from 1979-2006. I use data from the Current Population Survey (CPS). In the Current Population Survey, the Bureau of Labor Statistics (BLS) interviews 45 000 households each month. A quarter of the households are asked their earnings. The CPS has several advantages: It is designed to be representative for the United States and it contains information on individual characteristics. From the data set I extract the observations of those workers who have started a new job after coming from nonemployment within three months before the survey. Then, I aggregate the wage observations, controlling for changing composition of the sample over time. I do this by employing a two-step procedure: First, I take the observations of individual entry wages in one quarter and regress the individual wage on individual characteristics. Then, I take the average of the residuals of that quarter. This average is the value for the aggregate entry wage of that quarter. I do this for every quarter. This method has been proposed by Solon, Barsky and Parker (1994). They show that not controlling for individual characteristics leads to a severe underestimation of wage cyclicality. I regress the obtained wage series on output per hour in the non-farm business sector, the measure of aggregate productivity. I find an elasticity of 0.79, significantly different from zero, but not significantly different from unity. This leads me to take a stance in the Hall-Shimer debate about the matching model: In the matching model, the period-wage is not allocative. What matters for job-creation is the present-discounted value of all wage payments that are expected in the life time of the job. I show that the entry wage is proportional to the present discounted value of wage payments for the majority of possible calibrations of the matching model. Therefore, "fixing" the matching model by extending wage rigidity from ongoing job-relationship to newly created ones is at odds with the empirical evidence. Entry wages react to productivity and cannot be assumed to be as rigid as the wages of workers in ongoing job matches.

The second chapter **Employment Protection over the Workers' Life Cycles** aims at contributing to the debate about the pros and cons of employment protection. I investigate the hypothesis that employment protection provides an incentive to the firms to invest in their employees' human capital. The first contribution of this chapter is the development of a model that combines the idea of human capital formation over the life cycle with the labor market. This setting can be used to analyze many questions concerning the implications of labor market institutions on the formation of human capital, and on the evolution of the income distribution. When workers are young they enter the labor market with a human capital endowment. At the beginning of each period a skill shock arrives that makes a part of each worker's human capital obsolete. In order to keep the worker productive the firm has the possibility to train her. Alternatively, the firm can lay off the worker. In this setting I introduce a firing tax and a severance payment and analyze the effects this has on the amount of training and on the level of employment in the economy. A firing tax makes it more difficult for a firm to get rid of a worker when her productivity falls.

I calibrate the model and simulate it for different levels of a firing tax and a severance payment. I find that a moderate level of a firing tax exerts a positive influence on the amount of professional training. Firms try to avoid paying the firing tax by keeping the worker a longer time. This makes investments in the workers' human capital more rewarding. Additionally, by investing in the worker's human capital, the firm reduces the likelihood of a drop in productivity. However, I find this positive effect on professional training only in the case of young workers. Old workers don't get any training with or without a firing tax. Old workers benefit from a firing tax because it lowers their probability of layoff. If the firing tax is too high these positive effects are not observed. Instead, employment drops for young and for old workers and training is decreased. This is because with a firing tax it becomes increasingly difficult for the firms to earn enough profits to be compensated for the outlays of training. With a severance payment it is different. In the setting of this model a severance payment does not have an influence on the firm's layoff decision and consequently on the decision about how much to invest in the worker's skills.

The third chapter **Employment Protection and Training Incidence** examines the hypothesis of the second chapter empirically. In the first part, I use the German survey "report system professional training" and derive some stylized facts about professional training in Germany. The data show that most training is initiated by firms and financed by them. This provides motivation for the theoretical approach taken in chapter 2, focussing on the firms' incentives to train the worker. Then, I use data from the "Qualification and Career Survey" for a regression analysis. I exploit a change in the German legislation which happened in 1996. Before October of that year, establishments that had *five or less* employees were exempted from employment protection. On October 1st this exemption was extended to all establishments that had *ten or less* employees. I apply the method of difference-in-differences to assess whether the firms have changed their training policy. I estimate a linear probability model and a probit model. I find that the probability that an employee is sent to training to have decreased by 3.2% in the linear probability model and by 2.7% in the probit model. This empirical finding corroborates the theoretical result from the second chapter and shows that firms invest less in the workers' skills when there is no employment protection.

Chapter 1

Wage Rigidity and Job Creation[1]

This chapter documents that wages of newly hired workers out of non-employment strongly respond to aggregate labor market conditions. In the context of a labor market that is characterized by search frictions, the wage of newly hired workers is important because new hires are the 'marginal' workers that affect firms' decisions to create jobs. The wage of workers in ongoing jobs on the other hand, does not fluctuate much. Since there are many more workers in ongoing jobs than new hires, this makes the aggregate wage rigid. To document these facts, we construct time series for the wage of various subgroups of workers from the Current Population Survey (CPS), the largest publicly available US micro-dataset that allows to make this distinction.

Shimer (2005) and Costain and Reiter (2008) showed that a business cycle version of the search and matching model falls severely short of replicating labor market dynamics. In particular, for commonly used calibrations of the model, the predicted volatility of labor market tightness and unemployment is much lower than observed in the data. Shimer argued that period-by-period Nash bargaining over the wage leads wages to respond strongly to technology shocks, dampening the effect of these shocks on expected profits and therefore on vacancy creation. He suggested wage rigidity as a mechanism worth exploring to amplify the response of vacancy creation and unemployment to technology shocks.

Hall (2003) proposed a model of unemployment fluctuations with equilibrium wage stickiness, in which wages are completely rigid when possible and rebargaining takes place only when necessary to avoid match destruction (either through a layoff or a quit). In Hall's model there is a unique market wage, which implicitly extends this rigidity of wages on the job to wages of newly hired workers. A large number of more recent papers have appealed to some form of wage rigidity to improve the performance of labor market models with search frictions to match the business cycle facts in the data (Costain and

[1]This chapter is joint work with Christian Haefke and Thijs van Rens.

Reiter, 2008; Menzio, 2005; Rudanko, 2008; Farmer and Hollenhorst, 2006; Moen and Rosen, 2006; Braun, 2006; Gertler and Trigari, 2006; Blanchard and Galí, 2008; Hall and Milgrom, 2008; Shimer, 2009).

Few economists would doubt the intuitive appeal of this solution. A simple supply and demand intuition immediately reveals that technology shocks lead to larger fluctuations in the demand for labor if wages are rigid. Furthermore, it is a well documented fact that wages are less volatile than most models of the business cycle predict.[2] Using individual-level panel data on wages, several studies document evidence for wage rigidity (Bils, 1985; Solon, Barsky and Parker, 1994; Beaudry and DiNardo, 1991).

We argue, however, that the empirically observed form of wage rigidity does not generate additional volatility in employment and vacancies. The argument goes in two steps. First, we present new evidence that wages of newly hired workers are volatile and respond one-to-one to changes in productivity. We also find that wages for *ongoing* job relationships are indeed rigid over the business cycle, as in previous studies. Second, we show that in order to replicate these findings in a search model, we need to assume that wages in ongoing jobs are rigid but at the start of a job are set in a perfectly flexible manner. This kind of wage rigidity does not affect job creation. Thus, there is evidence for wage rigidity, but not of the kind that leads to more volatility in unemployment fluctuations.

The first contribution of this paper is to to construct a large, representative dataset of wages for newly hired workers out of non-employment. We use data on earnings and hours worked from the Current Population Survey outgoing rotation groups to calculate wages. We match the outgoing rotation groups to the basic monthly data files and construct four months employment history for each individual worker. We use these micro-data to construct quarterly time series for a wage index of new hires and workers in ongoing jobs and explore the cyclical properties of each series. After controlling for composition bias, we find an elasticity of the wage with respect to productivity of 0.8 for new hires and 0.2 for all workers.

Previous empirical studies on wage rigidity by macroeconomists have been concerned with *aggregate* wages (Dunlop, 1938; Tarshis, 1939; Cooley, 1995). If the importance of wages of new hires has been recognized at all, then a careful empirical study has been considered infeasible because of lack of data.[3] This practice has given rise to the conventional wisdom that wages fluctuate less than most models predict and that the data would therefore support modeling some form of wage rigidity.

Labor economists who have studied wages at the micro-level have mostly been con-

[2]Like the observation that employment (or total hours) is more volatile than predicted by the model, this is true for Real Business Cycle models, search and matching models as well as new Keynesian models.

[3]Hall (2005) writes that he does "not believe that this type of wage movement could be detected in aggregate data" (p.51). More specifically, Bewley (1999) claims that "there is little statistical data on the pay of new hires" (p.150).

cerned with wage changes of individual employees. Thus, the analysis has naturally been restricted to wages in *ongoing* employment relationships, which have been found to be strongly rigid. Notable exceptions are Devereux and Hart (2006), and Barlevy (2001) who both study job changers and find their wages to be much more flexible than wages of workers in ongoing jobs. Pissarides (2007) surveys these and other empirical micro-labor studies and concludes that wages of job changers respond much stronger to unemployment than wages of workers in continuing employment relationships.

The main difference between these studies and ours, is that we focus on newly hired workers, i.e. workers coming from non-employment, which is the relevant wage series for comparison to standard search models, rather than job-to-job movers. Since wages of non-employed workers are not observed, we need to use a different estimation procedure, which does not require individual-level panel data. Our procedure has the additional advantage that we can use the CPS, which gives us a much larger number of observations than the earlier studies, which use the PSID or NLSY datasets.

Like previous research, we find strong evidence for composition bias because of worker heterogeneity. Solon et al. (1994) show that failing to control for (potentially unobservable) heterogeneity across workers leads to a substantial downward bias in the cyclicality of wages. We document the cyclical patterns in the differences between new hires and the average worker in demographics, experience and particularly in the schooling level that cause this bias. Controlling for fluctuations in the skill level of the workforce is particularly important for our purposes since we study newly hired workers and at least some of the composition bias is likely to be driven by selection in the hiring process. This constitutes a potential weakness of our approach, because we cannot take individual-specific first differences and thus cannot control for unobservable components of skill as Solon et al. do. However, we use the PSID to demonstrate that controlling for observable skill is sufficient to control for composition bias. While unobservable components of skill might be important, they are sufficiently strongly correlated with education to be captured by our controls.

It is possible that not only the workers that are hired differ between recessions and booms, but the types of jobs that are created are different as well. In particular, there is some evidence that matches created in a boom pay higher wages and last longer than matches created in a recession (Beaudry and DiNardo, 1991; Davis, Haltiwanger and Schuh, 1996). In this paper, we do not address this issue for two reasons. First, we argue that the correct wage series to compare to one-sector models of the labor market is an aggregate time series. If there is heterogeneity across sectors in the amount of wage rigidity, the model behaves fundamentally different depending on the assumption one makes about the type of heterogeneity and the movement of labor between sectors. We postpone this interesting issue for future research. Second, since the CPS does not contain information on job characteristics, it is impossible to control for heterogeneous jobs in the same way we control for heterogeneous workers. The only thing we can do is to take a weighted average of the wage of new hires, constructing the weights such that the sample of newly hired workers is representative for the whole labor force in terms of industry and occupation. Keeping industry composition constant, the elasticity of the wage of new hires with respect to productivity drops substantially, but is still much higher than for workers in ongoing jobs.[4]

A final difference between this paper and the existing literature is that we focus on the response of wages to changes in labor productivity, whereas previous studies have typically considered the correlation between wages and the unemployment rate. With a search model, in which fluctuations are driven by exogenous changes in labor productivity but unemployment fluctuations are endogenous, our statistic is the more interesting one.[5] The elasticity of the wage to labor productivity has a natural interpretation in a wide range of models. It is not necessary for example, that changes in labor productivity are driven by technology shocks. Our estimates have the same interpretation for any shock that does not affect wages directly, but only through changes in productivity, e.g. government expenditure shocks or monetary policy shocks. We explore the robustness of our estimates to alternative measure of productivity and find very similar results. If we use unemployment rather than productivity as our regressor, we find similar estimates to those of Barlevy (2001) and Devereux and Hart (2006) for job changers. This indicates that the wage of new hires out of non-employment behaves similar to that of job-to-job movers and lends additional credibility to our estimates.

Our second contribution is to point out the implications of our findings for the unemployment volatility puzzle. In the standard stochastic search and matching model as in Shimer (2005), the elasticity of the wage with respect to productivity is close to one. We refer to this model, in which wages are set period-by-period through Nash bargaining, as the flexible wage model.[6] In order to match our estimate for the average wage elasticity of all workers, we need to assume that wages are rigid in ongoing job relationships. By rigidity we mean any kind of constraint on the wage bargaining process that implies that the division of match surplus between worker and firm shifts in favor of workers in periods when the surplus is small.

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[4] Recently, researchers have identified datasets that allow to simultaneously control for worker and firm heterogeneity. Carneiro, Guimarães and Portugal (2008) use matched employer-employee data for Portugal 1986-2005 and find that, controlling for composition bias due to both sources, entry wages are much more procyclical than wages in ongoing jobs, consistent with our estimates.

[5] Moreover, as pointed out by Hagedorn and Manovskii (2008), since we are ultimately interested in the predictions of the model for unemployment fluctuations, the calibration targets, including the cyclicality of wages, should not depend on unemployment. We discuss this issue further in Section 2.4.

[6] The number depends on the calibration. For example, if workers' bargaining is very low, as in Hagedorn and Manovskii (2008), the elasticity is much lower, although wages in that model are flexible.

Theory suggests several reasons why wages of newly hired workers should vary more strongly with productivity than wages of workers in ongoing employment relationships. Beaudry and DiNardo's (1991) model of implicit wage contracts is a good illustration of the type of wage rigidity that we believe to be plausible. Upon the start of a work-relationship the bargaining parties are relatively free in their wage determination. However, once the contract has been signed, wages can no longer be changed very much, in order to insure the worker against fluctuations in her income. In addition, internal labor markets can give rise to almost deterministic wage increases for continuing workers (Baker, Gibbs and Holmstrom, 1994). Many other theories of wage rigidity, because of efficiency wages (Yellen, 1984), unions (Oswald, 1985), motivational concerns (Bewley, 1999) or simply because rebargaining is costly, all provide plausible explanations for why wages are not changed very often during the relationship, but do not seem to apply to newly hired workers.

Wage rigidity in ongoing jobs has no effect on job creation and unemployment fluctuations in the standard search and matching model. What matters for employment dynamics is not the aggregate wage in the economy, but the wage of the marginal workers that are being hired. Formally, when firms decide on whether or not to post a vacancy, they face a trade-off between the search costs (vacancy posting costs) and the expected net present value of the profits they will make once they find a worker to fill the job. Thus, what matters for this decision is the expected net present value of the wage they will have to pay the worker they are about to hire. How this expected net present value is paid out over the duration of the match, is irrelevant (Boldrin and Horvath, 1995; Shimer, 2004a; Kudlyak, 2007). Previous studies that have used wage rigidity to explain the unemployment volatility puzzle, have either extended the rigidity to newly formed matches (Hall, 2005; Gertler and Trigari, 2006) or find very small effects (Rudanko, 2008).

What do our results imply for the unemployment volatility puzzle? We show that there is no need to assume rigidity in the wage of newly hired workers in order to match the wage data. Based on our estimates, we cannot rule out a moderate degree of rigidity in the wages of these workers, like for example the bargaining setup in Hall and Milgrom (2008), which reduces the influence of the value of unemployment on the outcome of the wage bargain. Nor can we rule out a calibration as in Hagedorn and Manovskii (2008) that relies on a wage elasticity slightly smaller than one in combination with a very small match surplus. In fact, we find some evidence that the response of wages of new hires to changes in productivity is smaller in the period before the Great Moderation. In the post 1984 period however, we find no evidence for rigidity in the wage of new hires and in the expected net present value of wage payments for newly created jobs.

The remainder of this chapter is organized as follows. In the next section we describe our dataset and comment on some of its strengths and weaknesses. We also provide a comparison of new hires and workers in ongoing jobs in terms of observable worker characteristics. In Section 2.4, we focus on the cyclical properties of the wage and present our estimates of the elasticity of the wage of new hires with respect to productivity. We also discuss how we control for composition bias and explore the robustness of our results. Section 1.3 discusses the implications of our findings for macroeconomic models of the labor market. Section 1.4 concludes.

1.1 Data

The prevailing opinion in the macro literature is that no data are available to test the hypothesis that the wage of new hires might be much more flexible than the aggregate wage (Bewley, 1999; Hall, 2005). Some anecdotal evidence seems to point against it.[7] To our knowledge, this paper is the first attempt to construct data on the aggregate wage for newly hired workers based on a large dataset that is representative for the whole US labor market.

1.1.1 Individual-level data from the CPS

We use data on earnings and hours worked from the CPS outgoing rotation groups from the BLS (2002), a survey that has been administered every month since 1979 which allows us to construct quarterly wage series for the period 1979–2006.[8] However, in most of the paper we focus on the post Great-Moderation period 1984–2006. Wages are hourly earnings (weekly earnings divided by usual weekly hours for weekly workers) corrected for top-coding and outliers and deflated using the deflator for aggregate compensation in the private non-farm business sector.

[7] According to Bewley, not only "there is little statistical data on the pay of new hires" (1999, p.150), but in addition, "the data that do exist show little downward flexibility.'" The data he refers to are average starting salary offers to college graduates in professional fields collected by the College Placement Council. While suggestive, these data are hardly representative for the labor force as a whole. Bewley also cites evidence in favor of wages of new hires being more flexible from Baker et al. (1994), who show that the average real pay of newly hired managers declined in recessions, even as the wage of existing employees continued to increase.

Some interesting additional suggestive evidence in favor of flexibility in the wage of new hires comes from Simon (2001). Simon documents that during the Great Depression, from 1929 to 1933, wages asked from situations-wanted ads for female clerical workers fell by almost 58%, much more than wages of existing female office workers (17.6%). However, Simon also argues that the wages offered to workers that were actually hired, although more flexible than wages paid to existing workers, fell by much less than wages asked and interprets his findings as evidence that employers rationed jobs. We are grateful to Emi Nakamura for drawing our attention to this paper.

[8] The BLS started asking questions about earnings in the outgoing rotation group (ORG) surveys in 1979. The March supplement goes back much further (till 1963), but does not allow to construct wage series at higher frequencies than annual. The same is true for the May supplement, the predecessor of the earnings questions in the ORG survey.

Figure 1.1:
Fraction of new hires among employed workers

Source: Basic Monthly Files of the CPS
Notes: The graph presents the number of new hires as a fraction of the total number of employed workers. The sample includes all individuals in the CPS who are employed in the private non-farm business sector and who are between 25 and 60 years of age (men and women), excluding supervisory workers. New hires are workers that started their current job no more than 3 months ago. The gaps in the graph are quarters when it is not possible to identify newly hired workers, see Appendix 1.A. The shaded areas indicate NBER recessions.

We match workers in our survey to the same individuals in three preceding basic monthly datafiles. This allows us to identify newly hired workers as those workers that were not employed for at least one of the three months before we observe their wage.[9] In addition, we have information on worker characteristics (gender, age, education, race, ethnicity and marital status), industry and occupation.

We restrict the sample to non-supervisory workers between 25 and 60 years of age in the private non-farm business sector but include both men and women in an attempt to replicate the trends and fluctuations in the aggregate wage. In an average quarter, we have wage data for about 25 000 workers, out of which about 19 000 can be classified to

[9] Abowd and Zellner (1985) show there is substantial misclassification in employment status in the CPS and provide correction factors for labor market flows. Misreporting of employment status also affects our results. A worker who, at some point during the survey period, incorrectly reports not to be employed will be classified as new hire by our procedure. Hence, such misreporting implies that some workers who are actually in ongoing relationships will appear in our sample of new hires. Given our argument that the wage of new hires reacts stronger to productivity fluctuations, such misreporting will bias the estimates against our result.

be in ongoing job relationships. The details on the data and the procedure to identify job stayers and new hires are in Appendix 1.A.

Figure 1.1 plots the number of new hires as a fraction of the total number of workers over time. On average, about 8% of employed workers found their job within the current quarter. This fraction seems to have been higher in the 1980s than in the later part of the sample. There is a clear cyclical pattern, with the fraction of new hires substantially higher in recessions.[10] In the quarter with the smallest fraction, we still have about 7% or 1300 newly hired workers. The only exceptions are the third and fourth quarter of 1985 and 1995. In these quarters, we cannot match individuals to the preceding four months because of changes in the sample design so that all our series that require workers' employment history in the previous quarter will have missing values in those quarters.

Table 1.1 reports summary statistics for some observable characteristics of workers. The evolution of these characteristics over time can be found in Figure 1.2. Clearly, newly hired workers are not representative for the labor force. New hires are more likely to be female, and much more likely to be African-American or Hispanic. They are also slightly younger and therefore have less labor market experience.[11] Finally, new hires have on average a year less schooling than the average for all workers. It is not surprising therefore, that new hires on average earn much lower wages. These numbers suggest that workers with lower wages also tend to work in higher turnover jobs, which makes them more likely to have recently started a new job in any given quarter.

1.1.2 Construction of the wage index

Workers are heterogeneous and newly hired workers are not a representative subsample of the labor force. If the composition of newly hired workers varies over the business cycle, then this heterogeneity will bias our estimate of wage cyclicality. Solon et al. (1994) show that this composition bias is substantial and that failing to control for changes in the composition of employed workers over the cycle makes wages seem less cyclical than they really are.

Taking into account individual heterogeneity, the wage w_{it} of an individual worker i at time t, depends in part on worker i's individual characteristics and in part on a residual

[10] This countercyclical pattern may be surprising compared to Shimer's (2007) finding that the hiring rate is strongly procyclical. The difference is because the hiring rate (or job finding rate) is the ratio of new matches over the number of unemployed workers, whereas here we plot the ratio of new matches over the number of employed workers. We could retrieve the job finding rate by multiplying the series in Figure 1.1 by a factor $(1-u)/u$, where u is the unemployment rate, which is a strongly procyclical factor.

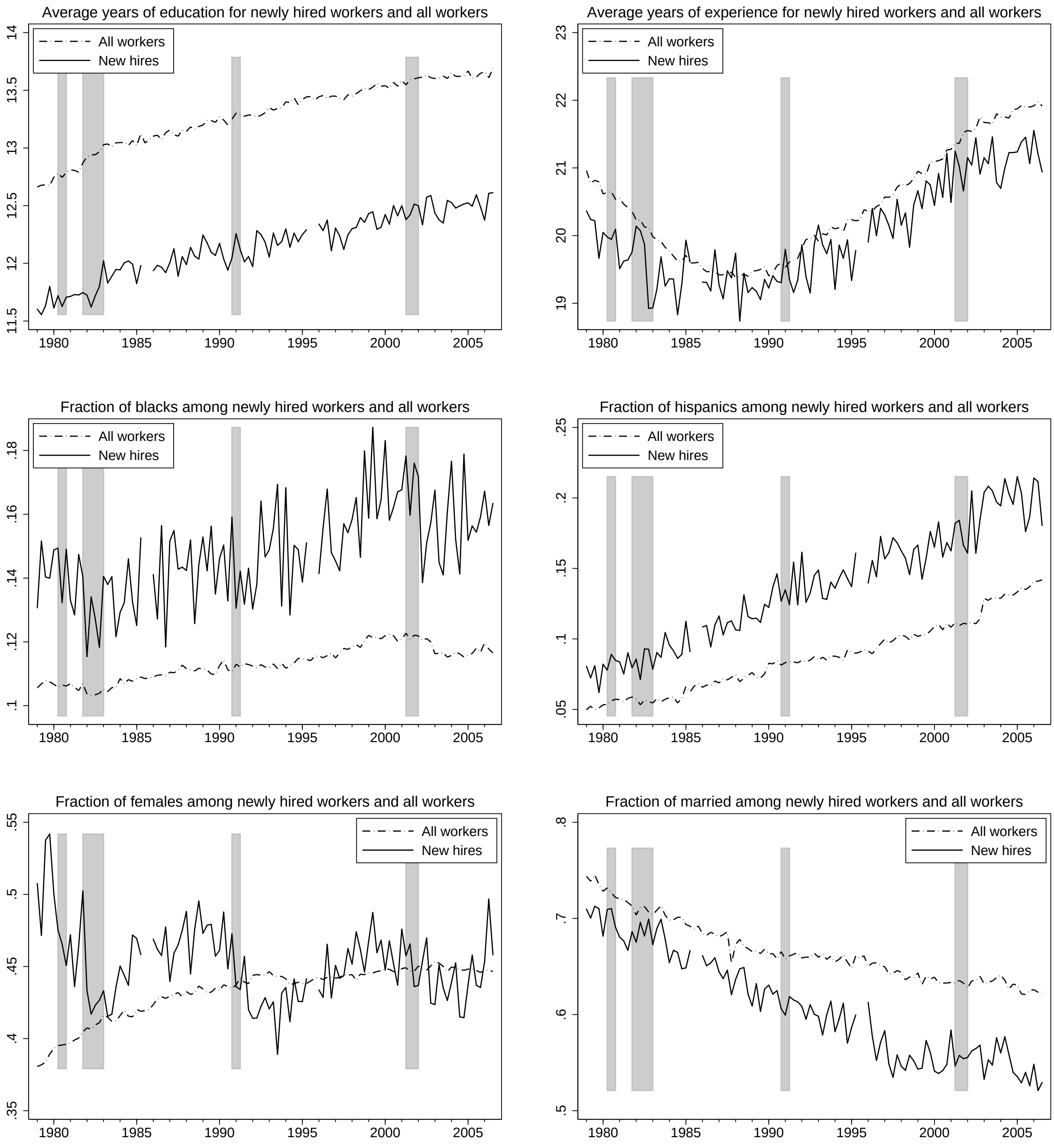
[11] If we include workers under 25 years old, the difference in experience becomes much larger. In this sample, new hires have an average experience level of 14.0 years, compared to 19.5 years for all workers because workers that find their first job are classified as new hires. For this reason, we exclude young workers from our baseline sample. The averages for the other characteristics are similar in both samples.

Table 1.1:
Worker characteristics, averages 1984–2006

	All workers	New hires
Percentage of female workers	44.0	44.9
Percentage of African-Americans	11.5	15.2
Percentage of Hispanics	9.5	15.0
Education (years of schooling)	13.4	12.2
Experience (years)	20.5	20.1

Source: Basic Monthly Files of the CPS.
Notes: The sample includes all individuals in the CPS who are employed in the private non-farm business sector and who are between 25 and 60 years of age (men and women), but excluding supervisory workers. Experience is potential labor market experience: age minus years of schooling minus 6.

Figure 1.2: Characteristics of all and newly hired workers over time



Notes: Education coding changes in 1992. In order not to loose that observation, we regressed the average education level in the sample on a third order polynomial in time and a post 1992 dummy and took the residuals, adding back up the polynomial but not the dummy to correct the resulting level shift. The shaded areas indicate NBER recessions. All graphs are based on the sample of individuals in the CPS who are employed in the private non-farm business sector and who are between 25 and 60 years of age (men and women). Supervisory workers are excluded. New hires are workers that started their current job no more than 3 months ago. The gaps in the graphs for newly hired workers are quarters when it is not possible to identify new hires, see Appendix 1.A.

that may or may not depend on aggregate labor market conditions.

$$\log w_{it} = x_i'\beta + \log \hat{w}_{it} \tag{1.1}$$

Here, x_i is a vector of individual characteristics that is constant or else varies deterministically with time, like age, and $\hat{w}_{it}$ is the residual wage that is orthogonal to those characteristics.

Following Bils (1985), the standard approach in the micro-literature has been to work with first differences of the wage, so that the individual heterogeneity terms drop out. However, taking first differences of individual wages limits the analysis to workers that were employed both in the current and in the previous period and thus does not allow to consider the wage of newly hired workers. Therefore, we take a different approach and proxy x_i by a vector of observables: gender, race, marital status, education and a fourth order polynomial in experience. We know from an extensive literature on the return to schooling, that these variables explain a substantial part of the idiosyncratic variation in wages, see e.g. Card (1999).

To obtain composition-bias corrected wages, we regress log wages on observable worker characteristics and take the residuals. Since we are interested in the comovement of wages with aggregate labor market conditions, we then aggregate by averaging these residuals by quarter for different subgroups of workers (e.g newly hired workers or workers in ongoing jobs).[12] Thus, the wage index for subgroup j, $\hat{w}_{jt}$, relates to the average wage of that group of workers, w_{jt}, as follows,

$$\log \hat{w}_{jt} = \log w_{jt} - (x_{jt} - \bar{x}_j)'\,\beta \tag{1.2}$$

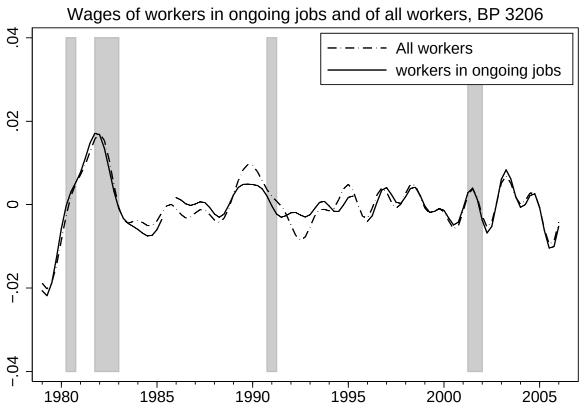
where x_{jt} is the average of the vector of observable characteristics for that subgroup of workers in each quarter and $\bar{x}_j$ denotes the sample average x_j. Notice that even if an individual worker's characteristics are time-invariant, the average characteristics for a group of workers may vary with time because the composition of the group changes.

1.1.3 Volatility of wages

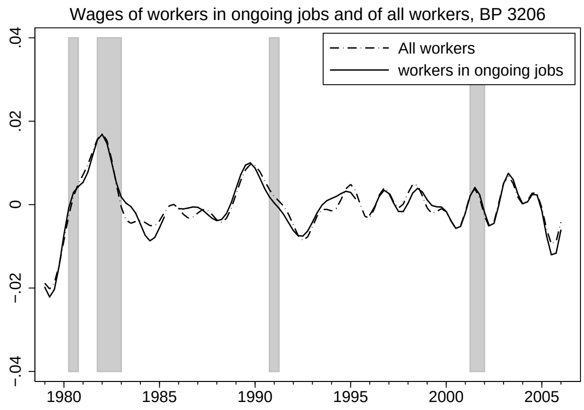
Figure 1.3 plots the wage index for workers in ongoing jobs and for newly hired workers. In order to focus on fluctuations at business cycle frequencies, we bandpass filtered the series to show only fluctuations with periodicities between 6 and 32 quarters. For comparison, the bottom graphs present the average log wage of these subgroups without correcting

[12] We consider average log wages to be consistent with the aforementioned micro-literature, although our results are robust for log average wages as well.

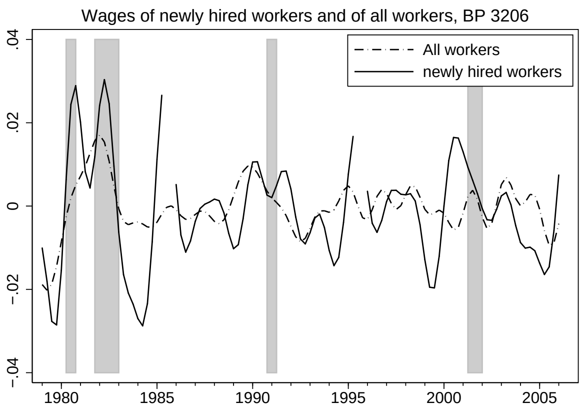
Figure 1.3: Wage cyclicality for different worker groups



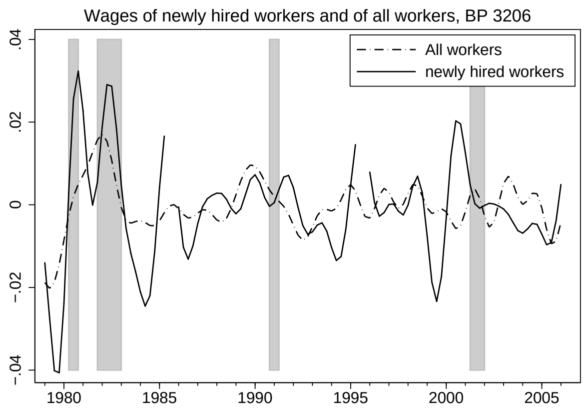
(a) workers in ongoing jobs, composition adjusted



(b) workers in ongoing jobs without composition adjustment



(c) new hires, composition adjusted



(d) new hires, without composition adjustment

Notes: The solid lines report the cyclical component of the wage for the corresponding subgroup of workers – with and without composition adjustment. The dashed line presents the average wage for all workers for comparison. The graphs in the left column control for composition bias as described in the main text, the graphs in the right column present the raw wage data. The cyclical component has been extracted from the wage series using a bandpass filter and shows fluctuations with periodicities between 6 and 32 quarters. The sample includes all individuals in the CPS who are employed in the private non-farm business sector and are between 25 and 60 years of age (men and women), excluding supervisory workers. New hires are workers that were non-employed at least once within the previous 3 months. The gaps in the graph are quarters when it is not possible to identify newly hired workers, see Appendix 1.A. The shaded areas indicate NBER recessions.

for composition bias, and each graph also shows the corresponding wage index for all employed workers.

The fluctuations in wages of workers in ongoing job-relationships look very similar to the fluctuations in the average wage of all employed workers. Neither series is very volatile and neither shows a clear comovement with the NBER business cycle dates. The wage of newly hired workers, however, is much more volatile than the aggregate wage.

Table 1.2:
Volatility of wages at business cycle frequencies

		BP filter		HP filter	
		Relative std. dev.	Auto correl.	Relative std. dev.	Auto correl.
Aggregate wage	1951-2001	0.41	0.92	0.43	0.91
	1984-2006	0.85	0.92	0.84	0.93
CPS, all workers	1984-2006	0.44	0.91	0.67	0.92
CPS, new hires	1984-2006	0.68	0.80	1.09	0.71

Notes: The aggregate wage is hourly compensation in the private non-farm business sector from the BLS productivity and cost program. Wages from the CPS are averages for all employed workers in the private non-farm business sector between 25 and 60 years old, excluding supervisory workers, corrected for composition bias as described in the main text. All series in logs. Bandpass filtered data include fluctuations with periodicities between 6 and 32 quarters. HP filtered data use a smoothing parameter of 100,000. In the CPS wage series the moments have been corrected for sampling error as described in Appendix 1.B.

To formalize this observation, Table 1.2 presents standard statistics for the volatility and persistence of various wage series. We present these statistics for detrended data using the bandpass filter and the Hodrick-Prescott filter. We have also corrected the statistics for the sampling error in the wage series that are constructed from the CPS, which biases the second moments, see Appendix 1.B.

The standard deviation of the wage of new hires is about 40% higher than for the wage of all workers and an F-test overwhelmingly rejects the null that the two variances are equal. The wage of new hires is also somewhat less persistent. The wage for stayers looks consistently very similar to the wage of all workers, because of the fact that in any given quarter, the vast majority of workers are in ongoing job relationships. These results are not specific to the filter used for detrending. Also, our conclusions are the same, and often even starker, if we use the median instead of the mean wage for each group. This is our first piece of evidence that the wage for newly hired workers is less rigid than the aggregate wage.

1.2 Response of wages to productivity

We now focus on a particularly relevant business cycle statistic: the coefficient of a regression of the log real wage index on log real labor productivity. This statistic has a natural interpretation as a measure of wage rigidity: if wages are perfectly flexible, they respond one-for-one to changes in productivity, whereas an elasticity of zero corresponds to perfectly rigid wages.

As pointed out by Hagedorn and Manovskii (2008), the elasticity of wages with respect to productivity is a better summary statistic for calibrating the search model than the correlation or elasticity of wages with other variables, like the unemployment rate, vacancies or labor market tightness. There are at least two reasons for this. First, in the model, other labor market variables are endogenous, but productivity is exogenous. Therefore, a regression of log wages on log productivity will deliver an unbiased estimate of the elasticity. Second, the coefficient of a regression of wages on unemployment or vacancies is inversely proportional to the variance of these variables. If we are evaluating the performance of the model to match these variances, then we do not want to target them in the calibration.

1.2.1 Estimation

In the context of this paper, there are additional advantages of using the elasticity rather than the correlation of wages with productivity. Our wage series are subject to (intertemporally uncorrelated) measurement error. This biases the volatility of wages and therefore their correlation with other variables (see Appendix 1.B). In a regression, however, measurement error in the dependent variable does not bias the coefficient. Moreover, the coefficient has a clear causal interpretation as an elasticity, it is straightforward to calculate standard errors, and we can easily control for other factors that affect wages, if necessary.

In order to avoid a spurious estimate of the elasticity if wages and productivity are integrated, we estimate our regression in first differences.

$$\Delta \log \hat{w}_{jt} = \alpha_j + \eta_j \Delta \log y_t + \varepsilon_{jt} \tag{1.3}$$

where $\hat{w}_{jt}$ is a wage index that controls for changes in the skill composition of the worker pool as in (1.2), j denotes the subgroup of workers (e.g. new hires) and y_t is labor productivity. Estimating in first differences has the additional advantage that we do not have to detrend the data using a filter, which changes the information structure of the data and therefore makes it harder to give a causal interpretation to the coefficient.

Notice that $\hat{w}_{jt}$ in equation (1.3) is itself an estimate from the underlying individual level wage data. Previous studies on the cyclicality of wages, starting with Bils (1985), have collapsed the two steps of the estimation procedure into one, and directly estimated the following specification from the micro data.

$$\Delta \log w_{ijt} = \tilde{\alpha}_j + \tilde{\eta}_j \Delta \log y_t + \tilde{\varepsilon}_{ijt} \tag{1.4}$$

where w_{ijt} is the uncorrected wage of individual i, belonging to subgroup j, at time t, as in (1.1). However, since the wage last quarter is unobserved for newly hired workers (because they were not employed then), this approach is not feasible for our purpose. Therefore, we implement our procedure as a two-step estimator and estimate (1.3) from aggregate wage series.

The main methodological difference between our study and previous work, which allows us to explore the cyclicality in the wage of newly hired workers, is that we use the first difference of the average wage, rather than the average first difference of the wage, as the dependent variable. This raises the question whether our approach to control for composition bias using observable worker characteristics is sufficient to control for all worker heterogeneity. To explore this issue, we re-estimated the results in Devereux (2001), the most recent paper that is comparable to ours. For this purpose, we use annual panel data from the PSID and apply the same sample selection criteria as Devereux does.[13]

The first column of Table 1.3 replicates Devereux's (2001) estimate of the response of the wage of workers in ongoing relationships to changes in the unemployment rate.[14] This response is estimated as in Devereux, from equation (1.4) using a two-step procedure. First, we take first differences for the wage of individual workers and average those by year. In the second step, we regress the annual averages of the change in the wage on the first difference of the unemployment rate.[15] The second column presents the same elasticity, estimated directly from the micro-data in a 1-step procedure, clustering the standard errors by year. As expected, this leaves both the point estimate and the standard error

[13] We are grateful to Paul Devereux for making his data available to us. To our knowledge, Devereux (2001) is the most recent paper with estimates comparable to ours from the PSID. Devereux and Hart (2006) use UK data. Barlevy (2001) regresses wages on state-level unemployment rates and includes interactions of the unemployment rate with unemployment insurance. Other more recent papers (Grant, 2003; Shin and Solon, 2007) use the NLSY. While the NLSY may be well suited to explore some interesting questions closely related to the topic of this paper (in particular, the cyclicality of the wage of job changers because of the much larger number of observations for this particular group of workers), it is not a representative sample of the US labor force.

[14] Previous studies have typically focused on the response of wages to unemployment as a cyclical indicator rather than productivity. Since here we are interested in evaluating the estimation methodology, we follow this practice for comparability.

[15] Devereux includes a time trend, experience and tenure as additional controls in the second step. In order to exactly replicate his estimates, we do the same. However, excluding these second step controls changes the estimates very little, indicating that first differencing in the first step largely takes care of heterogeneity across workers along these dimensions.

Table 1.3: Response of wages of job stayers to unemployment

	2-step est. first diff.	1-step est.	2-step est. levels	2-step est. controls
Elasticity wrt productivity	-0.81	-0.81	-0.37	-0.80
Std. error	0.20	0.19	0.62	0.20
Observations	42164			

Notes: Elasticities are estimated using annual panel data from the PSID, 1979-1991. The estimates in the first column replicate those reported in Devereux (2001), applying his 2-step procedure. In the first step, individual-specific first differences of the wage are regressed on time dummies. In the second step, the coefficients of these time dummies are regressed on the change in the national unemployment rate. This 2-step procedure can be replicated in one step, clustering the standard errors by quarter (column 2). In the third column we regress the log of the average wage on time dummies and then regress the coefficients of these dummies on the unemployment rate in first differences. The fourth column reports the results of our 2-step procedure, which includes individual characteristics (years of education, a fourth order polynomial in experience, and dummies for gender, race, marital status) as control variables in the first step.

virtually unaltered.

We now try to re-estimate these numbers using the 2-step estimation procedure we use for the CPS, first aggregating wages in levels and then estimating the elasticity in first differences. This procedure, which fails to control for composition bias, gives a very different point estimate, making the wage look less cyclical. However, when we include controls for education and demographic characteristics in the first step, the estimate in column 4 is once again very close to that in Devereux (2001). Surprisingly given that our procedure is less efficient than the one used by Devereux, we even get virtually the same standard error, suggesting the efficiency loss is small and we conclude that our procedure to control for individual heterogeneity using observable worker characteristics works well in practice.

1.2.2 Newly hired workers out of non-employment

Estimation results for the elasticity of the wage of new hires with respect to productivity are reported in Table 1.4. The regressions in this table include quarter dummies to control for seasonality but are otherwise as in equation (1.3). For each regression, we report the estimate for the wage elasticity, η_j, its standard error and the number of quarterly observations.

The elasticity of the wage of new hires with respect to productivity is much higher than

Table 1.4: Response of wages to productivity

	Wage per hour		Earnings per person	
	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.24	0.79	0.37	0.83
Std. error	0.14	0.40	0.17	0.51
Observations	1566161	117243	1566161	117243
Quarters	83	83	83	83

Notes: Elasticities are estimated using the two-step method described in the text. The number of observations is the number of individual workers in the first step. Labor productivity is output per our in the non-farm business sector from the BLS productivity and cost program. For the hourly wage we use labor productivity per hour and for regressions of earnings per person we use labor productivity per person. The second step includes seasonal dummies.

the elasticity of the wage of all workers. The wage of new hires responds almost one-to-one to changes in labor productivity, with an elasticity of 0.79 in the baseline estimates. The point estimates are never significantly different from one and often significantly different from zero. Thus, we do not find evidence for wage rigidity in the wage of new hires.

If hours per worker cannot be freely adjusted, one may argue that output per person and earnings per person provide better measures of wages and labor productivity. Results for these measures are also presented in Table 1.4 and provide a very similar picture as the hourly data. The results are also similar or even strengthened if we use median instead of mean wages or if we weight the regression by the inverse of the variance of the first step estimates to obtain the efficient second step estimator, see Table 1.5 in Appendix 1.D. Finally, the results are robust to different sample selection criteria for constructing average wages from the CPS, see Table 1.6 in Appendix 1.D.

Composition bias

Controlling for composition bias is crucial for our results. This is particularly true for newly hired workers, whose wage is more sensitive to changes in the composition of the unemployment pool. In Table 1.7 in Appendix 1.D, we present alternative estimates if we control only for a subset of observable components of skill. Not controlling for skill, reduces the elasticity of the wage of new hires from 0.79 to about 0.54.

We find that education is by far the most important component of skill. Not controlling for education gives an estimate that is similar to the elasticity we get if we do not control for skill at all. Controlling for experience or demographic characteristics has a much smaller effect on the elasticity. To our knowledge, this result is new. Whereas the importance of composition bias was well known, we document that it is largely driven by education level of unemployed workers, or at least by some component of skill for which the education level is a good proxy.

Wage response by gender and age groups

Much of the micro-literature on wage cyclicality has focused on male workers, arguing that female workers may be more loosely attached to the labor market. While we believe that for our purposes, including both genders provides the correct comparison for the model predicted behavior of wages, in Table 1.8 in Appendix 1.D we explore how this choice affects our results. The response of wages to productivity is substantially higher for men, although the difference is never significant. The differences are particularly large for newly hired workers. Thus, focusing on male workers only would further strengthen our evidence that wages of new hires are flexible.

Table 1.8 also presents some estimates including workers from a larger age range in the sample. In our baseline results, we focus on workers between 25 and 60 years old in order to exclude workers on their first job as well as workers close to retirement. Particularly excluding the young workers is important for our result. Adding workers between 20 and 25 years old to the sample, the elasticity of the wage of new hires decreases substantially, although not significantly. The result seems more robust to including older workers between 60 and 65 years old, with the elasticity remaining virtually unaltered. We argue that the behavior of both young and old workers is not described well by a simple model of labor supply and the correct comparison between model and data is to limit the analysis to workers that are in the middle of their career. To make sure we have set our age limits stringent enough, the last rows of the table present results based on workers between 30 and 45 years of age only. Since the sample size goes down substantially, the standard errors increase but the point estimates are almost identical.

Exogenous changes in productivity

Our baseline productivity measure is output per hour. As Hall (2007) has recently pointed out, the average and marginal product of labor are proportional to each other if the production function is Cobb Douglas and, under this assumption, output per hour is the appropriate measure of productivity to calculate elasticities. For our purposes, it is irrelevant what drives changes in productivity. The estimates have the same interpretation for any shock that does not affect wages directly, but only through changes in productivity. However, if labor productivity is endogenous, then the causal interpretation of the effect of productivity on wages is lost.

The most prominent possibility of endogeneity in labor productivity are diminishing returns to labor. In this case, the marginal product of labor is proportional to total factor productivity, but the factor of proportionality depends on employment. And since we are not sure what drives fluctuations in employment, this might introduce a spurious correlation between productivity and wages. To explore whether this type of endogeneity is important, we construct a measure of exogenous changes in log productivity, that is given by log output minus $1-\alpha$ times log hours, where $1-\alpha$ is the labor share in a Cobb-Douglas production function. If capital is fixed, this measure is proportional to total factor productivity (TFP).[16] As a more precise measure of TFP, we also use the quarterly version of the Basu, Fernald and Kimball (2006) series, constructed by Fernald (2007).

Since total factor productivity is arguably an exogenous source of fluctuations in labor productivity, we use these measure of TFP to instrument output per hour in our regressions. The results are presented in Table 1.9 in Appendix 1.D. For all instruments, our results become stronger and the elasticity of the wage of newly hired workers is now very close to unity.

1.2.3 Job-to-job changers

Throughout this paper, we have focused on newly hired workers out of non-employment. We argue that this is the relevant group of workers to compare to a standard search and matching model. However, as argued by Pissarides (2007), job-to-job movers, although not strictly comparable to a model without on-the-job search, may also be informative about wage flexibility of new hires. Some previous studies explored the cyclicality of wages of this group of workers (Bils, 1985; Devereux and Hart, 2006; Barlevy, 2001), see also Pissarides (2007) for a survey of these and other papers. Compared to new hires out of non-employment, job-to-job changers are an attractive group to study because one can control for composition bias by taking an individual-specific first difference.

To compare our results to those studies, we replicate and extend some of the results in Devereux (2001). Using annual panel data from the PSID, 1970-1991, Devereux finds an elasticity of the wage of all workers to changes in the unemployment rate of about -1 and for job stayers of about -0.8. These estimates are replicated in Table 1.10 in Appendix 1.D. Devereux does not report the cyclicality of job changers, but this elasticity can readily be estimated using his data and is also reported in the Table. With an elasticity

[16] Suppose production requires capital and labor and is of the Cobb-Douglas form with diminishing returns to total hours, $Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}$, where A_t is total factor productivity, K_t is capital and L_t is total hours. Log total factor productivity equals $\log A_t = \log Y_t - \alpha \log K_t - (1-\alpha)\log L_t$, whereas log labor productivity is given by $\log y_t = \log Y_t - \log L_t = \log A_t + \alpha \log K_t - \alpha \log L_t$. This illustrates the problem of endogenous fluctuations in total hours. If what we are interested in is total factor productivity, then log labor productivity is endogenous because of the $\alpha \log L_t$ term. Ignoring fluctuations in the capital stock, which are small compared to fluctuations in labor at high frequencies, we can construct a quarterly productivity series corrected for endogenous fluctuations in total hours as $\log \tilde{y}_t = \log Y_t - (1-\alpha)\log L_t = \log y_t + \alpha \log L_t$.

of -2.4, the wages of job changers are much more cyclical than those of all workers.

When we replace the right-hand side variable in these regressions with labor productivity, we find estimates that are very well in line with our baseline results. With an elasticity of about 0.96, the wage of job changers responds almost one-to-one to changes in productivity. The wage of all workers is slightly more responsive than in our baseline estimates (this may be due to the difference in the sample period), but is much less cyclical than the wage of job changers.[17]

Finally, we check whether there might be systematic differences between the PSID and the CPS by estimating the cyclicality in the wage of job changers from our CPS data. After 1994, the CPS asks respondents whether they still work in the same job as at the time of the last interview one month earlier. We use this question to identify job changers and find the estimates in the bottom panel of Table 1.10. Since we can only use data since 1994, the standard errors of these estimates are very large. The point estimates however, are well in line with the estimates from the PSID.

We find that the wage of job-to-job movers responds similarly to changes in labor market conditions as the wage of newly hired workers out of non-employment and -if anything- is even more cyclical. Intuitively, this makes sense. A story of wage rigidity that is based on rigidity in ongoing job relationships would affect neither new hires out of non-employment nor job-to-job movers. To the best of our knowledge, this result was not known before. It justifies the exercise in Pissarides (2007), to use the wage of job changers as a proxy for the wage of newly hired workers out of unemployment to calibrate a search and matching model without on-the-job search.

1.2.4 Great moderation and pre-1984 wage rigidity

Although our data starts in 1979, all estimates we presented so far were based on the 1984-2006 sample period. The reason is that around 1984 various second moments, relating to volatility but also to comovement of variables, changed in the so called Great Moderation (Stock and Watson, 2002). The change in the comovement seems to be particularly relevant for labor market variables, see Galí and Gambetti (2008).

As opposed to virtually all other macroeconomic aggregates, the volatility of wages did not decrease around the Great Moderation. This is true for the aggregate wage as well as for the wage of newly hired workers, see Table 1.2. We now explore whether the response of wages to productivity changed in this period.

Table 1.11 presents the elasticity of the wage with respect to productivity for our

[17] Notice that the sample size of job changers in the PSID is very small and the standard error of the elasticity of the wage of job changers to changes in productivity is much larger than our baseline estimate for the response of new hires out of non-employment, despite the fact that the estimation procedure in the PSID is more efficient, see Section 1.2.1.

baseline sample 1984-2006 as well as for the full period for which data are available, 1979-2006.[18] Even though we add only 5 years of data to the sample, wage respond substantially less to changes in productivity over the full sample than in the post 1984 period. The ordering of the response of the wages of the various groups of workers is unchanged: the wage of new hires responds more than the average wage, the wage of workers in ongoing jobs less. However, now even the wage of newly hired workers responds substantially less than one for one to changes in labor productivity. Like our baseline results, these estimates are robust across different measures of productivity, different sample selection criteria and different ways to calculate the wage series or to estimate the elasticity.

These findings provide some evidence for wage rigidity prior to 1984 and a flexibilization of the labor market during the Great Moderation. And because there seems to have been rigidity in wages of newly hired workers as well as in wages of workers in ongoing jobs, this flexibilization may have affected fluctuations in employment and other macroeconomic aggregates. While one has to interpret these estimates with care given the short period of data before 1984, they are consistent with studies that have pointed towards changes on the labor market as the ultimate cause of the Great Moderation (Galí and Gambetti, 2008) or have even attributed the Great Moderation to a reduction in wage rigidity (Gourio, 2008).

1.3 Implications for job creation and unemployment

What kind of models of labor market fluctuations are consistent with the observed behavior of wages? First of all, it must be that the labor market is subject to search frictions. On a frictionless labor market, workers can be costlessly replaced so that each worker is 'marginal' and differences in the wage of newly hired workers and workers in ongoing jobs cannot be sustained as an equilibrium. In this section we show that, in addition to search frictions, we also need rigidity in the wages of workers of ongoing jobs in order to match the low response of those wages to changes in productivity. We also show that wages must be close to flexible at the time of creation of a match to match the response of wages of newly hired workers.

The type of wage rigidity we find to be consistent with the data (flexible at the start of a match, rigid over the duration of the job) does not affect job creation and therefore is unlikely to explain the unemployment volatility puzzle. The basic intuition for this result is that in search and matching models, as in all models with long term employment relationships, the period wage is not allocative (Boldrin and Horvath, 1995). Labor market equilibrium determines the present value of these wage payments in a match, but the path

[18]Ideally, we would like to compare the elasticities to those for the pre-1984 period, but since we have only 5 years of data prior to 1984, this is infeasible.

at which wages are paid out over the duration of the match is irrelevant for job creation as long as the wage remains within the bargaining set and does not violate the worker's or firm's participation constraint (Hall, 2005). This means that wage rigidity matters only if it implies rigidity in the expected net present value of wage payment at the start of a match (Shimer, 2004*b*).

1.3.1 Job creation in a frictional labor market

To illustrate this point, consider a standard search and matching model with aggregate productivity shocks. Because we focus on job creation, we assume job destruction is exogenous and constant, as in Pissarides (1985). We think of fluctuations as being driven by shocks to productivity, as in Shimer (2005).[19] In this model, job creation is determined by vacancy posting. Risk-neutral firms may open a vacancy at cost $c > 0$ per period. With probability $q(\theta_t)$, a firm finds a worker to fill its vacancy, in which case a match is formed. The worker finding probability is strictly decreasing in labor market tightness $\theta_t = v_t/u_t$, where v_t is the total number of vacancies in the economy and u_t is the unemployment rate. Matches produce output y_t and the worker needs to be paid a wage w_t so that profits are $y_t - w_t$ in every period. With probability $\delta \in (0,1)$, matches are exogenously separated.

The decision how many vacancies to post is a trade-off between the vacancy posting costs on the one hand and the expected net present value of profits on the other. This trade-off is summarized by the job creation condition,[20]

$$c = q(\theta_t) \frac{\bar{y}_t - \bar{w}_t}{r + \delta}, \tag{1.5}$$

where $r > 0$ is the discount rate for future profits and $\bar{y}_t$ and $\bar{w}_t$ are the 'permanent' levels of productivity and the wage, defined as[21]

$$\bar{x}_t = \frac{r + \delta}{1 - \delta} \sum_{\tau=1}^{\infty} \left(\frac{1 - \delta}{1 + r} \right)^{\tau} E_t x_{t+\tau} \tag{1.6}$$

Notice that the firm uses an effective discount rate of $r + \delta$ because of the possibility that the match is destroyed. When expected profits go up, firms post more vacancies, which increases labor market tightness θ_t and therefore reduces the worker finding probability

[19]Our empirical results do not rely on this assumption. If business cycles were driven, for example, by demand shocks, these shocks would still affect wages only through the productivity of labor. However, in more general models the effect of wage rigidity on unemployment fluctuations is less clear, because there may be interaction effects with other frictions like nominal rigidities, see e.g. Thomas (2008).

[20]We write the model in discrete time but assume that all payments are made at the end of the period, so that the expressions look similar to the continuous time representation.

[21]These are the constant levels for productivity and wages that give rise to the same expected net present value as the actual levels. We borrow the term permanent levels from the consumption literature, cf. permanent income.

until in expectation profits are equal to the vacancy posting costs c again. The derivation of equation (1.5) is standard; details may be found in Appendix 1.C.1.

We now turn to the question what kind of wage determination mechanism we need to assume in order to match our findings for the response of wages to changes in productivity. If wages are rigid in the sense that the permanent wage $\bar{w}_t$ does not increase in response to an increase in (permanent) productivity $\bar{y}_t$, then profits and therefore vacancy creation respond more strongly to this increase in productivity. Because we can think of the job creation equation (1.5) as a labor demand curve, this is the sense in which search models replicate the Walrasian intuition for why wage rigidity amplifies unemployment fluctuations. The difference with the Walrasian framework is that not current profits $y_t - w_t$ matter for vacancy creation, but the expected net present value of profits over the duration of the match.

1.3.2 Flexible wages

Because search frictions drive a wedge between the reservation wages of firm and worker, there is a positive surplus from a match. The standard assumption in the literature is that each period, firm and worker engage in (generalized) Nash bargaining over the wage, so that each gets a fixed proportion of the surplus. Under this assumption, we can derive the following wage curve or labor supply equation,

$$\bar{w}_t = (1-\beta)\, b + \beta \bar{y}_t + \beta c \bar{\theta}_t \tag{1.7}$$

where b is the value to the worker of being unemployed in each period, which includes utility from leisure as well as the unemployment benefit, and β is workers' bargaining power in the wage negotiations. The wage depends on labor market conditions because of the worker's outside option to look for another job. The derivation of equation (1.7) is again standard, see Appendix 1.C.2. Combined with the job creation equation (1.5), the wage curve fully describes the equilibrium of the model.

If wage bargaining takes place in every period, the wage in this model is flexible in the sense that it immediately adjusts to changes in productivity and labor market conditions. To explore the quantitative predictions of the flexible wage model for the response of wages to changes in productivity, we assume that y_t follows an exogenous stochastic process that is consistent with labor productivity data, and simulate the model. The details of the calibration and simulation procedure are described in Appendix 1.C.3. Since some of the parameters are calibrated directly to data, we show only the model predictions for different values of the unemployment benefit b and workers' bargaining power β, keeping the other calibration targets fixed at the values used by Shimer (2005).

The simulation results in Table 1.13 in (Appendix 1.D) reveal several interesting patterns. First, the elasticity of the wage of newly hired workers with respect to current productivity is very close to the elasticity of the permanent wage with respect to permanent productivity for all calibrations. Since we observe the former, but the latter matters for job creation, this finding is encouraging in light of the exercise in this paper. (In Section 1.3.3, we discuss why the two elasticities are not exactly the same.)

Second, we find that the response of the wage of newly hired workers is identical to the response of the wage of job stayers to changes in productivity. This finding is not surprising. Since all firms and all workers are identical, they have the same outside options at each point in time. And since each firm-worker pair bargains over the wage in each period, they always agree on the same wage. This prediction of the model however, is clearly at odds with our estimates.

Finally, the simulation results show that the elasticity of the wage with respect to productivity is close to one for a wide range of parameter values. In models with a frictionless labor market, this elasticity is always exactly equal to one if the expenditure share on labor in the production function is constant. In that case, the marginal product of labor is proportional to its average product, and the wage equals the marginal product. However, on a labor market with search frictions, the wage is no longer equal to the marginal product of labor. What we show here is that for a wide range of calibrations, the wage is roughly proportional to the marginal product. This provides an intuitive benchmark for the empirical results: in a model with flexible wage setting, wages should respond almost one-for-one to changes in labor productivity.[22] And this prediction is consistent with our estimate of the response of the wage of newly hired workers, suggesting that wage setting is flexible for those workers.

Summarizing, a model with search frictions on the labor market, but perfectly flexible wage setting, predicts a response of wages of newly hired workers to changes in productivity that is in line with our estimates. The model fails however, to capture the substantially lower response of wages of workers in ongoing matches. This suggests that wages in ongoing jobs are rigid. We now proceed to introduce this kind of wage rigidity into the model.

1.3.3 Rigid wages in ongoing jobs

We maintain the assumption that wages are determined by Nash bargaining, but only at the start of a match. Thereafter, wages are rigid so that they do not change much

[22] The only calibrations for which the elasticity is substantially smaller than one are very small values of workers' bargaining power as, for example, in Hagedorn and Manovskii (2008), who calibrate β to a wage elasticity of 0.3. This calibration is ruled out by our estimates for the response of wages of newly hired workers. Notice however, that this it is not crucial for their result that the flexible wage model can match the volatility of vacancies and unemployment. Even with large values for β, the model can generate large amounts of volatility as long as b is close enough to 1 so that the match surplus is small.

anymore for the duration of the match. Under this assumption the wage curve is exactly like (1.7). Notice that the permanent wage depends not only on current but also on expected future labor market conditions, because by accepting a job the worker forfeits the option value to find another job in the future. The fact that the period wage does not appear in the equilibrium conditions for θ_t illustrates that the path at which wages are paid is irrelevant for labor market tightness θ_t and therefore job creation. The period wage is not determined in this model, unless we explicitly model the type of wage rigidity we have in mind.

As an extreme case, assume that wages are perfectly rigid in ongoing jobs. This is the model analyzed in Shimer (2004*b*). As in that paper, we need to make an assumption to avoid inefficient match destruction. Shimer assumes that search frictions are large enough that, given the stochastic process for labor productivity, the wage in ongoing matches never hits the bounds of the bargaining set. Here, we make the simpler assumption of full commitment on the part of both worker and firm, so that matches never get destroyed endogenously (as in the simple case in Rudanko 2008). This model is relatively simple to solve. The simulation results are presented in Table 1.12 in Appendix 1.D.

Three main results follow from the simulations. First, wage rigidity in ongoing jobs drives a wedge between wages of newly hired workers and of workers in ongoing jobs, the latter now responding substantially less to changes in productivity than the former. Second, some of the wage rigidity seems to 'spill over' to newly hired workers and the response of the wages of these workers to changes in productivity is now substantially less than one. Third, this type of wage rigidity does not affect the response of the permanent wage to changes in permanent productivity and therefore also does not affect the volatility of job creation. We discuss each of these results in turn.

Since we assumed wages of workers in ongoing jobs to be rigid, it is not surprising that the wage of this group of workers responds less to productivity than the wage of newly hired workers, which is not subject to the rigidity. The only reason that the elasticity for job stayers is not equal to zero is that the group of stayers changes over time: this period job stayers includes last period's new hires. But because the fraction of new hires is small compared to the overall size of the labor force, this effect is small. The much lower responsiveness of the wage of workers in ongoing jobs than the wage of new hires to changes in productivity is consistent with our estimates, improving the ability of the model to match the wage data compared to the model with perfectly flexible wages.

To understand why the wage of newly hired workers responds less than one-for-one to changes in productivity, despite the fact that wages setting is flexible for these workers, it is useful to consider the following identity,

$$\frac{d\log \bar{w}_t}{d\log \bar{y}_t} = \frac{d\log \bar{w}_t / d\log w_t^0}{d\log \bar{y}_t / d\log y_t} \frac{d\log w_t^0}{d\log y_t} \tag{1.8}$$

where w_t^0 denotes the wage of newly hired workers, so that $d \log w_t^0 / d \log y_t$ is the elasticity of the wage of newly hired workers with respect to current productivity, which we observe, and $d \log \bar{w}_t / d \log \bar{y}_t$ is the elasticity of the permanent wage with respect to permanent productivity, which determines fluctuations in job creation. The elasticity of the permanent wage differs from that of the wage of new hires by a factor that reflects the relative persistence in wages and productivity in ongoing jobs.

Since in this model the permanent wage equals the wage of new hires (since the wage in a given job never changes anymore after the time of hiring), the numerator of this ratio equals one. If productivity were a random walk, then $\bar{y}_t = y_t$ and the denominator would be one as well. In that case, the observed elasticity of the wage of newly hired workers would exactly reflect the elasticity of the permanent wage. If there is mean reversion in productivity, $d \log \bar{y}_t / d \log y_t$ is smaller than one, so that the observed elasticity provides a lower bound for the elasticity of the permanent wage. This result is consistent with Kudlyak (2007), who constructs an estimate for the permanent wage, which she calls the 'wage component of the user cost of labor', and finds that "the wage component of the user cost is more cyclical than the wages of newly hired workers, which in turn are more cyclical than the wages of all workers."

Equation (1.8) can also be used to explain why, in the flexible wage model, the response of the wage of new hires to changes in current productivity is close, but not exactly equal, to the response of the permanent wage to changes in permanent productivity. In that model, persistence in wages is equal to the persistence of the productivity process plus any additional persistence coming from the model dynamics. But since the search and matching model exhibits virtually no endogenous propagation, the ratio of the persistence of wages over productivity is very close to one.

The model with perfectly rigid wages in ongoing jobs slightly underpredicts the response of the wage of both workers in ongoing jobs (0.16) and new hires (0.65) to changes in productivity compared to our estimates (0.25 and 0.79 respectively). There are many reasons why wages in ongoing jobs would be less than perfectly rigid. One possibility would be to relax the assumption of full commitment and assume that wages in ongoing jobs are rebargained if but only if the wage hits the bounds of the bargaining set, as in an earlier version of Hall's (2005) paper. What is important for the argument here, is that we match the response of wages to productivity, assuming that wages are rigid *only* in ongoing jobs. As we argued in the introduction, this assumption is consistent with most micro-foundations for wage rigidity.

Wage rigidity in ongoing jobs does not affect job creation. The reason is that job creation, which is completely pinned down by equations (1.5) and (1.7), is affected only by the permanent wage. And rigidity of the wage in ongoing jobs does not imply any rigidity in the permanent wage. The intuition for this result is that equilibrium tightness is determined by those firms who have not yet found a worker and are deciding whether or not to post a vacancy. These firms are trading off payment of the search cost c with the expected future profits after hiring a worker. What matters for these profits, is the expected future wage payments to be made to the worker.

For comparison, we also present simulation results for a model with rigid wages at the start of a match. Here, we think of wage rigidity as countercyclical bargaining power of workers, as suggested by Shimer (2005). We model this in the simplest possible way, by making β depend negatively on the level of productivity, and calibrate the degree of rigidity to match the response of job creation to changes in productivity. Without any additional rigidity in wages of ongoing jobs, this model roughly matches the response of the wage of workers in ongoing jobs but implies a much lower response of the wage of newly hired workers than we find in the data.

1.3.4 The unemployment volatility puzzle

Wage rigidity in ongoing jobs, which is consistent with the wage data, does not affect job creation and therefore does not generate more volatility in unemployment. What are the implications of our results for the unemployment volatility puzzle more generally? A useful starting point is to calculate the response of the job finding rate to changes in labor productivity from the job creation equation (1.5). Assume the matching function is Cobb-Douglas with constant returns to scale and let μ denote the share parameter of the unemployment rate. Then, the response of the hiring rate $p(\theta_t) = \theta_t q(\theta_t) = \theta_t^{1-\mu}$ is given by

$$\frac{d \log p(\theta_t)}{d \log y_t} = \frac{1-\mu}{\mu} \left[\frac{\bar{y}_t}{\bar{y}_t - \bar{w}_t} - \frac{\bar{w}_t}{\bar{y}_t - \bar{w}_t} \frac{d \log \bar{w}_t}{d \log \bar{y}_t} \right] \tag{1.9}$$

Two things matter for the volatility of the job finding rate in response to productivity shocks: the elasticity of the permanent wage with respect to permanent productivity, and the size of permanent profits $\bar{y}_t - \bar{w}_t$. Our estimates indicate that the wage elasticity $d \log \bar{w}_t / d \log \bar{y}_t$ is close to one in the data.

There are two ways to interpret our results. First, one might conclude that wages must be perfectly flexible and so that the wage elasticity is virtually equal to one, as in Table 1.12. This interpretation is certainly consistent with our estimates. In this case, the response of the job finding rate to changes in productivity in (1.9) reduces to $(1-\mu)/\mu$. The only parameter that matters for fluctuations in job creation is the elasticity of the matching function. Petrongolo and Pissarides survey empirical estimates of μ and find that the share of unemployment in the matching function is no greater than 0.5. Thus, the response of $p(\theta_t)$ to changes in y_t predicted by the model, is at most 1. In the data, the ratio of the standard deviation of the job finding rate $p(\theta_t)$ over the standard deviation of labor productivity y_t is about 5.9. Thus, in this interpretation, the model cannot be calibrated to match the volatility of job creation. Since (1.9) was derived only from the job creation equation (1.5), which was derived without any assumptions on wage determination or workers' behavior, the only way to fix the model would be to change modeling of labor demand side of the market.

Our estimates are consistent with an alternative interpretation as well. A value for $d\log\bar{w}_t/d\log\bar{y}_t$ that is close to, but not equal to one, cannot be rejected based on our estimates. Thus, a moderate degree of wage rigidity, for example as implied by the bargaining setup in Hall and Milgrom (2008), may help generate more volatility in job creation. In this case, an alternative calibration may also contribute to solving the puzzle. By making profits a very small share of total match output, the response of the job finding rate to changes in productivity as in equation (1.9) can be made arbitrarily large. This is the intuition for why the small surplus calibration of Hagedorn and Manovskii (2008) generates large fluctuations in unemployment.

Finally, a generalization of the model that allows for endogenous job destruction could contribute to the volatility of unemployment, although the contribution to fluctuations in job creation -if any- is likely to be small. Fujita and Ramey (2007), in response to Shimer (2007), show that fluctuations in the separation rate may explain up to 50% of the volatility of unemployment. In our model, the separation rate is constant, so that fluctuations in unemployment are attributed entirely to fluctuations in the job finding rate by the following accounting identity.

$$u_{t+1} = u_t + \delta\left(1 - u_t\right) - p\left(\theta_t\right) u_t \tag{1.10}$$

Since exogenous fluctuations in the separation rate δ_t, imply a counterfactual positive correlation between unemployment and vacancies (see e.g. Shimer (2005)), the most promising way to relax this assumption seems to be to endogenize job destruction, e.g. as in Mortensen, Dale and Nagypál (1994). This raises the question whether wage rigidity may affect job creation through its effect on job destruction, for example because worker and firm take into account the effect on the probability that their match will be destroyed when they bargain over the wage at the start of the match. We argue that this effect is likely to be small. First, it seems implausible on theoretical grounds that wage rigidity would affect job destruction, since the effect would imply inefficient destruction of matches, i.e. separations that could be avoided by re-bargaining the wage when necessary, see Hall (2005). Second, as shown by Mortensen and Nagypál (2007) and Pissarides (2007), while endogenous separations may have an important impact on unemployment fluctuations, this generalization of the model does not affect the dynamics of labor market tightness. Since in this paper, we focus on the dynamics of job creation, relaxing the assumption of an exogenous separation rate will not affect our results.

1.4 Conclusions

In this paper we construct an aggregate time series for the wage of workers newly hired out of non-employment. We find that these wages of newly hired workers react one-to-one to productivity fluctuations, whereas wages of workers in ongoing job relationships react very little to changes in productivity. Controlling for cyclical variation in the skill composition of the workforce is important for this result, and we show that the average skill level of the workforce is captured well by the average number of years of education. Finally, we relate our finding to existing studies on the cyclicality of wages of job changers and show that wages of new hires out of non-employment behave similar to wages of job-to-job movers.

Our results point against rigidity in the wage of newly hired workers as an explanation for the volatility of unemployment over the business cycle as forwarded by Hall (2005), Gertler and Trigari (2006) and Blanchard and Galí (2008). However, a moderate degree of wage rigidity or alternative calibrations as in Hagedorn and Manovskii (2008) or Hall and Milgrom (2008) are within the confidence interval of our estimates. Finally, our baseline estimates are based on the post 1984 period and we find some evidence that wages of newly hired workers were more rigid prior to that year.

Appendix 1.A
Description of the data

We use wage data for individual workers in the CPS outgoing rotation groups from 1979 to 2006. We match these workers to the three preceding basic monthly datafiles in order to construct four months (one quarter) of employment history, which we use to identify newly hired workers.

1.A.1 Wages from the CPS outgoing rotation groups

We consider only wage and salary workers that are not self-employed and report non-zero earnings and hours worked. Both genders and all ages are included in our baseline sample. Our wage measure is hourly earnings (on the main job) for hourly workers and weekly earnings divided by usual weekly hours for weekly workers. For weekly workers who report that their hours vary (from 1994 onwards), we use hours worked last week. Top-coded weekly earnings are imputed assuming a log-normal cross-sectional distribution for earnings, following Schmitt (2003), who finds that this method better replicates aggregate wage series than multiplying by a fixed factor or imputing using different distributions. Notice that the imputation of top-coded earnings affects the mean, but not the median wage.

Outliers introduce extra sampling variation. Therefore, we apply mild trimming to the cross-sectional distribution of hours worked (lowest and highest 0.5 percentile) and hourly wages (0.3 percentiles). These values roughly correspond to USD 1 per hour and USD 100 per hour at constant 2002 dollars, the values recommended by Schmitt (2003). We prefer trimming by quantiles rather than absolute levels because (*i*) it is symmetric and therefore does not affect the median, (*ii*) it is not affected by real wage growth and (*iii*) it is not affected by increased wage dispersion over the sample period. We also check that our results are robust to using median wages, which are less affected by outliers.

We do not correct wages for overtime, tips and commissions, because (*i*) the relevant wage for our purposes is the wage paid by employers, which includes these secondary benefits, (*ii*) the data necessary to do this are not available over the whole sample period, and (*iii*) this correction has very little effect on the average wage (Schmitt, 2003). We also do not exclude allocated earnings because (*i*) doing so might bias our estimate for the average wage and (*ii*) allocation flags are not available for all years and (*iii*) even if they are only about 25% of allocated observations are flagged as such (Hirsch and Schumacher 2004).

Mean and median wages in a given month are weighted by the appropriate sampling weights (the earnings weights for the outgoing rotation groups) and by hours worked, following Abraham, Spletzer and Stewart (1999) and Schmitt (2003). We explore robustness to the weights and confirm the finding of these papers that hours weighted series better replicate the aggregate wage. Average mean or median wages in a quarter are simple averages of the monthly mean or median wages. Consistent with the literature, we consider mean log wages rather than log mean wages.

In order to correct the business cycle statistics for the wage for sampling error (see Appendix 1.B), we calculate standard errors for mean and median wages. Standard errors for the mean are simply the standard deviation of the wage divided by the square root of the number of observations. Medians are also asymptotically normal, but their variance is downward biased in small samples. Therefore, we bootstrap these standard errors.

We seasonally adjust our wage series by regressing the log wage on quarter dummies. Nominal wages are deflated by the implicit deflator for hourly earnings in the private non-farm business sector (chain-weighted) from the BLS productivity and costs program. Using different deflators affects the results very little, but decreases the correlation of our wage series with the aggregate wage.

Our baseline sample includes non-supervisory workers in the private non-farm business sector. This subsample of workers gives the best replication of the aggregate wage in terms of its correlation with hourly compensation from the establishment survey and in terms of its volatility, persistence and comovement with other variables.[23] We identify private sector workers using reported 'class of worker'. We construct an industry classification that is consistent over the whole sample period (building on the NBER consistent industry classification but extending it for data from 2003 onwards) and use it to identify farm workers. Similarly, we identify supervisory workers using reported occupation. Because of the change in the BLS occupation classification in 2003, there is a slight jump in the fraction of supervisory workers from 2002:IV to 2003:I. It is not possible to distinguish supervisory workers in agriculture or the military, so all workers in these sectors are excluded in the wage series for non-supervisory workers.

Finally, in order to control for composition bias because of heterogeneous workers (see Section 1.1.2), we need additional worker characteristics to use in a Mincerian earnings regression. Dummies for females, blacks, Hispanics and married workers (with spouse present) are, or can be made, consistent over the sample period. We construct a consistent education variable in five categories as well as an almost consistent measure for years of schooling following Jaeger (1997) and calculate potential experience as age minus years of schooling minus six.

[23]Detailed results for this replication exercise are available in a previous version of this paper (July 2007), available from our websites.

1.A.2 Identifying newly hired workers

We match the individuals in the outgoing rotation groups to the three preceding basic monthly data files using the household identifier, household number (for multiple households on one address), person line number (for multiple wage earners in one household), month-in-sample and state. To identify mismatches, we use the s|r|a criterion proposed by Madrian and Lefgren (2000): a worker is flagged as a mismatch if gender or race changes between two subsequent months or if the difference in age is less than 0 or greater than 2 (to allow for some measurement error in the reported age). Madrian and Lefgren show that this criterion performs well in the trade-off between false matches and false mismatches. Within the set of measures that they find to perform well, s|r|a is the strictest. We choose a strict criterion because mismatches are more likely to be classified as newly hired workers (see below) and are therefore likely to affect our results substantially.

We can credibly match about 80% of workers in the outgoing rotation group to all three preceding monthly files. Because of changes in the sample design, we cannot match sufficiently many individuals to the preceding four months in the third and fourth quarter of 1985 and in the third and fourth quarter of 1995, so that the wage series for validly matched workers, job stayers and new hires have missing values in those quarters. In our regressions, we weight quarters by the variance of the estimate for the mean or median wage so that quarters with less than average number of observations automatically get less weight.

Including the outgoing rotation group itself, the matched data include four months employment history (employed, unemployed or not-in-the-labor-force), which we obtain from the BLS labor force status recode variable. We use this employment history to identify newly hired workers and workers in ongoing job relationships. New hires are defined as workers that were either unemployed or not in the labor force for any of the preceding three months. Job stayers are identified as workers that were employed for all four months. Notice that the two groups are not comprehensive for the group of all workers, because workers that cannot be matched to all preceding months can not always be classified.

Appendix 1.B
Correcting business cycle statistics for sampling error

We estimate wages for all workers, job stayers and new hires from an underlying microdata survey. Therefore, our wage series are subject to sampling error. Given the way we construct these series, we know three things about the sampling error. First, because there is no overlap between individuals included in the outgoing rotation groups in two subsequent quarters, the sampling error is uncorrelated over time.[24] Second, because the sampling error in each period is the error associated with estimating a mean (or median), it is asymptotically normally distributed. Third, we have an estimate for the standard deviation of the sampling error in each quarter, which is given by the standard error of the mean (or median) wage in that quarter. Notice that taking first difference exacerbates the measurement error, increasing the standard deviation by a factor $\sqrt{2}$. Because of these three properties, and because the estimated standard errors are stable over time, we can treat the sampling error as classical measurement error, which is independent and identically distributed.

Let w_t denote an estimated wage series, $w_t = w_t^* + \varepsilon_t$, where w_t^* is the true wage and ε_t is the sampling error in the wage, which is uncorrelated over time and with w_t^* and has a known variance σ^2. The business cycle statistics we consider are the standard deviation of w_t^*, the autocorrelation of w_t^* and the correlation of w_t^* with x_t, an aggregate variable that is not subject to measurement error. These statistics can be calculated from the estimated wage series w_t and the estimated standard deviation of the sampling error σ as follows.

$$var\left(w_t\right) = var\left(w_t^*\right) + \sigma^2 \Rightarrow sd\left(w_t^*\right) = \sqrt{R} \cdot sd\left(w_t\right) \tag{1.11}$$

$$cov\left(w_t, w_{t-1}\right) = cov\left(w_t^*, w_{t-1}^*\right) \Rightarrow corr\left(w_t^*, w_{t-1}^*\right) = \frac{corr\left(w_t, w_{t-1}\right)}{R} \tag{1.12}$$

$$cov\left(w_t, x_t\right) = cov\left(w_t^*, x_t\right) \Rightarrow corr\left(w_t^*, x_t\right) = \frac{corr\left(w_t, x_t\right)}{\sqrt{R}} \tag{1.13}$$

where $R = \left(var\left(w_t\right) - \sigma^2\right)/var\left(w_t\right) \in (0,1)$ is the fraction of signal in the variance of w_t. Unless explicitly specified, we use the correction factors $\sqrt{R}$, $1/R$ and $1/\sqrt{R}$ for all reported business cycle statistics. This bias correction is small for the wages of all workers and job stayers, because sample sizes are large and therefore σ^2 is small, but substantial for the wage of new hires. Notice that the bias correction decreases the reported standard deviations towards zero but increases the reported autocovariances and correlation coefficients away from zero. For bandpass filtered series no correction is necessary because the filter removes the high-frequency fluctuations due to measurement error from the data. Regression coefficients for the wage on labor productivity are not biased in the presence of classical measurement error in the dependent variable so no

[24]Individuals in the CPS are interviewed four months in a row, the last one of which is an outgoing rotation group, then leave the sample for eight months, after which they are interviewed another four months, the last one of which is again an outgoing rotation group. Therefore, about half of the sample in quarter t (individuals in rotation group 8) is also included in the sample in quarter $t-4$ (when they were in rotation group 4) and the other half is included in the sample in quarter $t+4$. Thus, the sampling error may be correlated with a four quarter lag, but not between subsequent quarters. We ignore this correlation structure and treat the sampling error as uncorrelated over time.

correction is necessary.

Appendix 1.C
Model details from Section 1.3

1.C.1 Derivation of the job creation equation

Free entry drives the value of a vacancy to zero, which implies that the period cost c must equal the probability that the vacancy transforms in a match times the expected value of that match.

$$c = q\left(\theta_t\right) E_t J_{t+1} \tag{1.14}$$

The value to the firm of having a filled job J_t, is given by the following Bellman equation.

$$(1+r)J_t = y_t - w_t + (1-\delta)E_t J_{t+1}. \tag{1.15}$$

Solving equation (1.15) forward gives an expression for the value of a filled job.

$$J_{t+1} = \frac{\bar{y}_{t+1} - \bar{w}_{t+1}}{r+\delta} \tag{1.16}$$

$$\bar{w}_{t+1} = \bar{y}_{t+1} - (r+\delta)\frac{c}{q\left(\theta_t\right)}. \tag{1.17}$$

Substituting (1.16) into (1.14) gives the job creation equation in the main text.

1.C.2 Derivation of the wage equation

The derivation of the wage curve (Equation 1.7) follows Pissarides (2000, sec. 1.4). Here the steps are slightly different because we consider a stochastic version of the search model. First of all, it is convenient to note, that Nash bargaining implies

$$W_{t+1} - U_{t+1} = \frac{\beta}{1-\beta} J_{t+1} \tag{1.18}$$

To derive the wage equation, start from the Bellman equation for the value of being unemployed.

$$(1+r)\,U_t = b + \theta_t q\left(\theta_t\right) E_t W_{t+1} + \left(\left(1 - \theta_t q\left(\theta_t\right)\right) E_t U_{t+1}\right) \tag{1.19}$$

Rearrange to obtain:

$$E_t U_{t+1} - (1+r)U_t = -b - \theta_t q\left(\theta_t\right) E_t\left(W_{t+1} - E_t U_{t+1}\right) \tag{1.20}$$

Now use (1.18) to replace the worker surplus on the right-hand side of the equation. Then use (1.14) to replace the value of a job.

$$E_tU_{t+1} - (1+r)\,U_t = -b - \theta_t q(\theta_t)\left(\frac{\beta}{1-\beta}\frac{c}{q(\theta_t)}\right) = -b - \frac{\beta}{1-\beta}c\theta_t \tag{1.21}$$

This equation will be useful momentarily.

Next consider the Bellman equation for having a job.

$$(1+r)W_t = w_t + (1-\delta)E_tW_{t+1} + \delta E_tU_{t+1} \tag{1.22}$$

Subtract $(1+r)\,U_t$ from both sides to obtain:

$$(1+r)(W_t - U_t) = w_t + (1-\delta)\,E_t(W_{t+1} - U_{t+1}) + E_tU_{t+1} - (1+r)\,U_t \tag{1.23}$$

Now replace the last two terms using (1.21) and rearrange,

$$(1-\delta)\,E_t(W_{t+1} - U_{t+1}) - (1+r)(W_t - U_t) = -w_t + b + \frac{\beta}{1-\beta}c\theta_t \tag{1.24}$$

solve forward and substitute the definitions of $\bar{w}_t$ and $\bar{\theta}_t$, to get an expression for the worker's surplus of being in a match.

$$(r+\delta)\,E_t(W_{t+1} - U_{t+1}) = \bar{w}_t - b - \frac{\beta}{1-\beta}c\bar{\theta}_t \tag{1.25}$$

Again using Nash bargaining (1.18) and eliminating J_{t+1} using (1.16), we get,

$$\frac{\beta}{1-\beta}(\bar{y}_t - \bar{w}_t) = \bar{w}_t - b - \frac{\beta}{1-\beta}c\bar{\theta}_t \tag{1.26}$$

which after solving for $\bar{w}_t$ gives equation (1.7) in the main text.

1.C.3 Numerical solution and simulations

Because these more general models can no longer be solved analytically, we simulate them. We assume (as in Shimer (2005), that labor productivity follows an AR(1) type process, bounded below by the flow utility of unemployment.

$$y_t = b + e^{z_t}(1-b) \tag{1.27}$$

$$z_t = \rho z_{t-1} + \varepsilon_t \tag{1.28}$$

where productivity shocks are normally distributed, $\varepsilon_t \sim N(0, \sigma^2)$. Our calibration of the model parameters is identical to Shimer (2005). As an alternative we present results for a small surplus calibration in the spirit of Hagedorn and Manovskii (2008). The vacancy posting cost is chosen to yield steady state tightness of unity. We simulate the model at a weekly frequency and aggregate to quarterly observations. The reported elasticities are averages over 1000 simulations of length 89.

Appendix 1.D

Additional tables

Table 1.5: Robustness to alternative estimators

	Wage per hour		Earnings per person	
WLS	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.25	0.79	0.36	0.86
Std. error	0.14	0.40	0.17	0.50
Median	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.13	0.89	0.15	0.56
Std. error	0.20	0.45	0.24	0.70
Median, WLS	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.11	0.89	-0.05	0.57
Std. error	0.24	0.49	0.22	0.72

Notes: Elasticities are estimated using the two-step method described in the text. WLS weights the second step regression by the inverse of the variance of the first step estimates. Median uses the median wages instead of mean wages by quarter.

Table 1.6: Robustness to alternative sample selection criteria

	Wage per hour		Earnings per person	
Including supervisory workers	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.10	0.57	0.39	0.70
Std. error	0.13	0.40	0.18	0.49
Including public sector	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.06	0.70	0.33	0.57
Std. error	0.12	0.48	0.15	0.54
New hires out of unemployment	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.24	0.77	0.37	0.69
Std. error	0.14	0.55	0.17	0.70

Sources: BLS and Basic Monthly Files of the CPS, 1979-2006
Notes: All specifications are estimated using the two-step method described in the text. The table compares the results of different compositions of the sample from which the aggregate wage is constructed. For all regressions robust standard errors have been computed. Labor productivity is output per our in the non-farm business sector as published by the BLS. Control variables used in the first step are dummies for gender, race, marital status and education, and a fourth order polynomial in experience. The second step includes seasonal dummies.

Table 1.7: Worker heterogeneity and composition bias

	Wage per hour		Earnings per person	
No controls for skill	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.14	0.67	0.27	0.73
Std. error	0.15	0.41	0.18	0.50
No controls for experience	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.26	0.91	0.40	0.94
Std. error	0.14	0.42	0.17	0.53
No controls for education	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.16	0.54	0.30	0.58
Std. error	0.15	0.40	0.18	0.48
Only controls for education	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.22	0.92	0.35	0.98
Std. error	0.14	0.44	0.17	0.53

Notes: Elasticities are estimated using the two-step method described in the text. The table compares the results for varying specifications of the first step regression. The first specification excludes all controls for individual characteristics from the regression. The second and third specification omit controls for labor market experience and education, respectively. The fourth specification omits controls for both experience and demography but includes controls for education.

Table 1.8: Differences across gender and age groups

	Men and women		Men only	
Age: 25 – 60	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.24	0.79	0.26	1.29
Std. error	0.14	0.40	0.14	0.55
Age: 20 – 60	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.17	0.34	0.21	0.71
Std. error	0.13	0.35	0.13	0.47
Age: 25 – 65	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.23	0.70	0.25	1.15
Std. error	0.13	0.40	0.14	0.56
Age: 30 – 45	All workers	New hires	All workers	New hires
Elasticity wrt productivity	0.13	0.70	0.20	1.72
Std. error	0.17	0.62	0.19	0.71

Notes: Elasticities are estimated using the two-step method described in the text. The table compares the results for different compositions of the sample from which the CPS wages are constructed, varying gender and age ranges.

Table 1.9: Exogenous changes in productivity

	Wage per hour		Earnings per person	
Corrected labor productivity	All Workers	New Hires	All Workers	New Hires
Elasticity wrt productivity	0.33	1.07	0.43	1.00
Std.err	0.18	0.47	0.19	0.55
TFP	All Workers	New Hires	All Workers	New Hires
Elasticity wrt productivity	0.26	1.03	0.33	0.82
Std.err	0.19	0.48	0.20	0.55
TFP, corrected for factor utilization	All Workers	New Hires	All Workers	New Hires
Elasticity wrt productivity	0.19	1.06	0.29	1.07
Std.err	0.18	0.58	0.23	0.70

Notes: Elasticities are estimated using the two-step method described in the text. The table compares the results for varying measures of productivity in the second step regression. The first specification uses a rough measure of TFP, log output minus $1-\alpha$ times log hours worked, where $1-\alpha$ is the labor share in a Cobb-Douglas production function. The second and third specifications use the quarterly version of the Basu et al. (2006) productivity series. In all cases, these productivity measures are used to instrument labor productivity.

Table 1.10: Response of wages of job-to-job movers

	All workers	New hires	Job changers
PSID, 1970-1991			
Elasticity wrt unemployment	-1.01		-2.43
Standard error	0.21		0.68
Elasticity wrt labor productivity	0.43		0.96
Std. error	0.21		0.74
Observations	52525		6406
Years	21		21
CPS, 1994-2006			
Elasticity wrt unemployment	0.42	-1.31	-2.02
Standard error	0.54	1.74	2.09
Observations	863600	62753	57619
Quarters	45	45	45

Notes: The table compares the response of the average wage of job changers to the average wage for all workers and for new hires. The estimates from the PSID use Devereux's (2001) annual data, take individual-specific first differences and include a linear time trend. The estimates from the CPS are estimated using the two-step method described in the text.

Table 1.11:
Wage rigidity before the great moderation

	All workers	New hires
1984-2006		
Elasticity wrt productivity	0.24	0.79
Standard error	0.14	0.40
Observations	1566161	117243
Quarters	83	83
1979-2006		
Elasticity wrt productivity	0.18	0.49
Standard error	0.11	0.32
Observations	1904458	146108
Quarters	102	102

Notes: The table compares the results of varying the sampling period. All specifications are estimated using the two-step method described in the text. For all regressions robust standard errors have been computed. Labor productivity is output per our in the non-farm business sector as published by the BLS. Control variables used in the baseline specification are dummies for gender, race, marital status and education, and a fourth order polynomial in experience. The second step includes seasonal dummies.

Table 1.12: Simulation results for rigid wage models

Model	$\frac{d\log\bar{w}}{d\log\bar{y}}$	$\frac{d\log w^n}{d\log y}$	$\frac{d\log w^s}{d\log y}$	$\frac{d\log w^a}{d\log y}$	$\frac{d\log\theta}{d\log y}$	$\frac{\sigma_u}{\sigma_y}$
Shimer, AER calibration	0.985	0.986	0.986	0.986	1.646	0.413
Small Surplus calibration	0.384	0.389	0.389	0.389	46.516	11.706
Countercyclical Bargaining power	0.601	0.228	0.228	0.228	24.028	6.002
On the job wage rigidity	0.985	0.648	0.159	0.163	1.646	0.413

Notes: The table reports simulated elasticities for different models, varying the type of wage rigidity. Parameters are calibrated as in Shimer (2005), except for the small surplus calibration where the flow utility of unemployment is 0.98 of per period productivity and the worker bargaining power is 0.05. In each simulation the vacancy posting cost is chosen to normalize steady state labor market tightness to unity. The reported elasticities are averages of 1000 simulations of 89 quarters. All simulated data are in log first differences. The models are simulated at weekly frequency and aggregated to quarterly data before computing the statistics.

Table 1.13: Simulated elasticities for the flexible wage model

b	β	$\frac{d\log\bar{w}}{d\log\bar{y}}$	$\frac{d\log w}{d\log\bar{y}}$	$\frac{d\log w}{d\log y}$	$\frac{d\log\bar{w}}{d\log w}$	$\frac{d\log\bar{y}}{d\log y}$	$\frac{d\log\theta}{d\log y}$	$\frac{\sigma_\theta}{\sigma_y}$	$\frac{\sigma_u}{\sigma_y}$
0.200	0.050	0.727	1.126	0.732	0.646	0.650	1.171	1.171	0.240
0.200	0.100	0.843	1.300	0.845	0.648	0.650	1.191	1.192	0.243
0.200	0.300	0.951	1.464	0.951	0.649	0.650	1.221	1.221	0.250
0.200	0.500	0.978	1.505	0.978	0.650	0.650	1.231	1.231	0.251
0.200	0.700	0.990	1.524	0.990	0.650	0.650	1.236	1.236	0.252
0.200	0.900	0.997	1.535	0.997	0.650	0.650	1.239	1.239	0.254
0.400	0.050	0.592	0.920	0.598	0.643	0.650	1.561	1.561	0.319
0.400	0.100	0.751	1.160	0.754	0.647	0.650	1.588	1.588	0.324
0.400	0.300	0.919	1.415	0.920	0.649	0.650	1.627	1.627	0.333
0.400	0.500	0.963	1.483	0.964	0.650	0.650	1.641	1.642	0.335
0.400	**0.700**	**0.984**	**1.514**	**0.984**	**0.650**	**0.650**	**1.647**	**1.647**	**0.338**
0.400	0.900	0.996	1.532	0.996	0.650	0.650	1.652	1.653	0.338
0.600	0.050	0.499	0.777	0.505	0.642	0.650	2.341	2.342	0.479
0.600	0.100	0.677	1.047	0.680	0.646	0.650	2.381	2.381	0.486
0.600	0.300	0.889	1.369	0.890	0.649	0.650	2.443	2.444	0.499
0.600	0.500	0.949	1.461	0.949	0.650	0.650	2.462	2.463	0.503
0.600	0.700	0.977	1.504	0.978	0.650	0.650	2.471	2.472	0.505
0.600	0.900	0.994	1.530	0.994	0.650	0.650	2.478	2.478	0.507
0.800	0.050	0.431	0.672	0.437	0.641	0.650	4.684	4.686	0.957
0.800	0.100	0.616	0.954	0.620	0.646	0.650	4.761	4.763	0.975
0.800	0.300	0.861	1.327	0.862	0.649	0.650	4.878	4.880	0.998
0.800	0.500	0.935	1.440	0.936	0.649	0.650	4.921	4.923	1.007
0.800	0.700	0.971	1.494	0.971	0.650	0.650	4.945	4.948	1.011
0.800	0.900	0.992	1.527	0.992	0.650	0.650	4.949	4.951	1.013
0.980	**0.050**	**0.384**	**0.600**	**0.390**	**0.640**	**0.650**	**46.749**	**46.782**	**9.542**
0.980	0.100	0.570	0.884	0.574	0.645	0.649	47.518	47.554	9.721
0.980	0.300	0.837	1.291	0.839	0.648	0.650	48.772	48.811	9.979
0.980	0.500	0.923	1.422	0.924	0.649	0.649	49.103	49.144	10.046
0.980	0.700	0.966	1.487	0.966	0.649	0.650	49.352	49.392	10.107
0.980	0.900	0.991	1.525	0.991	0.650	0.650	49.486	49.528	10.129

Notes: The table reports simulated elasticities for different calibrations of the model. We vary the flow value of unemployment b and workers' bargaining power β. Other parameters are calibrated as in Shimer (2005). The reported elasticities are averages of 1000 simulations of 89 quarters. All simulated data are in log first differences. The model is simulated at weekly frequency and aggregated to quarterly data before computing the statistics. In bold face the calibrations of Shimer (2005) and Hagedorn and Manovskii (2008). w is the average wage in the model, y is average productivity, $\bar{w}$ and $\bar{y}$ are the permanent values of these variables (see Section 1.3.2), θ is labor market tightness and σ_x denotes the standard deviation of variable x.

Chapter 2

Employment Protection over the Workers' Life Cycles

During recent years the reform of labor market institutions has been a central issue in the European policy debate. One of the most controversial labor market institutions is employment protection (EP). Proponents of EP praise it as an instrument that prevents firms from unfairly dismissing workers, quick profit interests in view and not considering the social and monetary costs this implies for the workers. Opponents of EP perceive it as a means of lobby groups to protect the jobs of insiders at the cost of outsiders who have difficulties to find a job. They accuse it of hampering necessary adjustments in the labor market, and deem it the predominant culprit for the unemployment rates in Europe having risen almost continuously since the 1970s, and recovering only recently.

The empirical evidence, however, is less clear-cut. Most studies find that EP reduces unemployment incidence and increases unemployment duration. The effect on the overall unemployment rate is ambiguous (Nickell and Layard, 1999). Also, theoretical assessment provides mixed results, depending on the type of model used and on the choice of the parameter values (Ljungqvist, 2002).

When advocating a labor market policy it is important to know the implications of the different policy options, what they imply for firms and workers, which costs they entail, and what are their effects on distributional outcomes. Here, the focus is not on efficiency considerations, rather I adopt the perspective of the policy maker who wants to know what will be the consequence of abolishing employment protection or what will be the result of introducing EP in an economy where it does not yet exist. Generally, employment protection policies are aimed at supporting stable and long-lasting employment relationships, they should enhance investment in relationship-specific capital and "promote workers effort and cooperation"(OECD, 2004). In an empirical assessment of labor market institutions, Layard and Nickell (1999) find a positive effect of EP on productivity. They write:"... more training ... is only worth providing if the employment relation is longterm." Firms will only be inclined to invest in the workers human capital if the worker will stay some time with them. EP is one instrument that lengthens job tenures. It makes it more difficult to the firm to lay off a worker once a negative productivity shock arrives. Therefore, a firm will be rather inclined to invest in the worker's human capital in order to increase his productivity. This provides the motivation to analyze consequences of EP on the firms' incentives to invest in the workers' human capital.[1]

The question about how labor market institutions affect training behavior is gaining importance due to two seminal trends: the ageing of societies in the industrialized countries and the increasing pace of technological progress. In the future, employers will have to rely more on the work of older workers.[2] This is especially important in Europe where the societies are ageing faster than in the US. The situation becomes more critical as technology progresses at a much higher speed than before. Consequently, knowledge acquired at the beginning of the working career loses relevance faster (Ludwig and Pfeiffer, 2005). Workers have to retrain continuously to keep themselves up to date and to learn new production technologies. Therefore, if politics wants to reform the labor market, it is important to consider consequences for lifelong learning and on-the-job training. Older workers face a special problem here: as they are only few years away from retirement, often it does not pay off for them to learn the new techniques. This could be a reason for the fact that the labor force participation of older workers has been decreasing during the last decades although life expectancy has been increasing (Hurd, 1997). When a new technological wave arrives a firm could be inclined to lay off the old workers and to hire new workers who are more productive, or to hire young workers. In the presence of employment protection the firm would refrain from laying off the workers and rather train them on the new production technologies even if they are old. Thus, EP could lead to more training and therefore to a more skilled labor force in general, and this way even lead to a reduction of unemployment, especially of older workers.

The contribution of this chapter is to develop a model which is able to analyze the effect of employment protection on the firms' incentives to invest in the workers' human capital. In order to examine this question I use a life-cycle model in the style of Ben-Porath (1967) and combine it with a labor matching model. This allows me to analyze the effect of EP on training and on employment rates for different age groups specifically. A further contribution of this chapter is the development of a model that can be used to analyze various questions that concern the interactions of labor market institutions and

[1] It would also be possible to analyze the workers' incentives to invest in his own human capital. That analysis could be done using the same model. In this chapter I restrict the analysis to the firm's incentives because there is evidence that most training is general and financed by firms. (See Chapter 3 about on-the-job training in Germany.)

[2] A symptom of this development is the increase of the legal retirement age in Germany.

human capital formation.

In the simulation of the model I find that EP protection leads to more investment in human capital especially for middle-aged and older employees. A severance payment has a stronger effect than a firing tax of the same size. EP is detrimental to employment for most age groups. However, a moderate level of a firing tax can increase employment of older workers.

The remainder of this chapter is structured as follows: the next section reviews relevant literature, Section 2.2 develops a model, combining life-cycle aspects with labor market matching. Section 2.3 calibrates and simulates the model. Section 2.4 interprets the results, and Section 2.5 offers some implications.

2.1 Related literature

There are several types of employment protection: "procedural inconveniences which the employer faces when trying to dismiss employees; notice and severance pay provisions; and prevailing standards of and penalties for unfair dismissal" (OECD, 1999). The essence of EP policies is to impose costs on the firms if they lay off workers. I will focus on two types of EP: firing taxes and mandated severance payments. Other costs related to dismissal like administrative costs or legal expenses can also be conceived as a firing tax, but are not considered here.

Severance payments and firing taxes have different effects on labor market equilibrium. Lazear (1990) showed that in a classical labor market without frictions a severance payment has no effect on the equilibrium because employer and employee will design the wage contract in such a way that the mandatory transfer is *undone*. The worker compensates the firm by reducing the wage by an amount corresponding to the size of the severance payment.

Therefore, in the beginning, researchers have focused on the analysis of firing taxes, costs that the firm incurs when it wants to lay off a worker but that are not a transfer from the firm to the worker. Ljungqvist (2002) gives a comprehensive overview of how a firing tax influences labor market equilibrium. He analyzes the mechanisms in three different labor market models: a model with employment lotteries, a search model and a matching model. In all three model types the introduction of a firing tax reduces the surplus from a match and reduces the reservation productivity, i.e. the level below which the worker is laid off. Consequently average productivity falls. In principle, all three model types can yield an increase and a decrease in employment, depending on the choice of parameter values. However, for plausible calibrations, the model with employment lotteries leads to less employment and the search model to an increase in employment. For the matching model, Ljungqvist shows that the effect on the unemployment rate depends crucially on the wage setting mechanism, namely whether the firm's outside option in the wage bargain is decreased by the firing tax.[3] In this study, I will use the setup in which he finds a negative effect on employment. Therefore, the positive employment effect which I find for the group of older workers should be a relatively robust result.

As for the severance payment, Garibaldi and Violante (2005) show that Lazear's 1990 result of neutrality carries over to a labor market with matching frictions. However, their result hinges on a wage setting mechanism where the outside options are not altered by the severance payment. Since the firms' and the workers' outside options are influenced by the severance payment in the model of this chapter, the neutrality is not maintained, here.

The general picture which emerges in the empirical literature is that EP tends to reduce reallocation in the labor market and tends to lengthen job tenures and unemployment spells. It has a negative impact on employment of young workers and prime-age women (OECD, 1999, 2004; Nickell, 1997) while less so (Heckman and Pages, 2000) or even a positive impact (OECD, 1999) for the employment of prime age men. However, the evidence is far from clear-cut: Bauer, Bender and Bonin (2007) exploit a revision of the German Employment Protection Act and check whether the change had an impact on worker flows, however, they do not find a significant effect. "Robust estimates of the impact of EP on employment and unemployment have proven elusive" (OECD, 1999).

The other strand of literature which is relevant for this study is the theory of human capital accumulation. The classical theory of human capital is described by Becker (1964). He analyzes human capital accumulation in a completely flexible and competitive setting. For analytical purposes he distinguishes between general and specific human capital. Specific human capital is defined as an individual's skills and knowledge which are useful only at one specific firm. General human capital summarizes skills and knowledge which are transferable and useful also at other firms. This distinction between general skills and firm specific skills has been used as an analytical device in the bulk of the subsequent literature on human capital accumulation. Both types of human capital have different implications for individual earnings. Since general human capital is transferable to the next firm, the next firm is willing to reward the worker for this capital by paying him the corresponding marginal productivity. Thus, general human capital increases the worker's outside option and therefore the current employer must pay the worker more if she does not want to lose him; she must pay him at least the outside option. Specific human capital is of no use in any other firm, it does not increase the worker's marginal productivity in any other firm, he cannot expect a higher wage in any other firm. It does not increase his outside option. Therefore, the current employer does not have to pay a higher wage to the worker and she can reap all the proceeds resulting from specific human capital. The

[3] I will discuss this issue in Section 2.2.6, when wage setting is introduced in the model.

result of this reasoning is that the worker has no incentive to invest in specific skills and that the employer has to pay for all of the training in specific skills. The opposite applies to general skills: since the employer does not get any of the rent of the worker's general skills, she has no incentive to invest in the worker's general skills. The worker has to pay all of the training in general skills himself. However, in equilibrium the resulting level of investment in skills is optimal. This result is robust to the introduction of mobility costs, i.e. if the worker incurs a cost if he changes employer (Acemoglu and Pischke, 1999). Crucial for this result is the assumption of a perfectly competitive labor market.

Ben-Porath (1967) incorporates the accumulation of general human capital into a model of the worker's life cycle. The worker's human capital relates directly to his earnings. In the course of his life the worker invests optimally in training and education in order to increase his earnings potential. Ben-Porath provides this way an explanation for increasing wages in the worker's lifetime. He considers only general training whose costs are borne by the worker. Firm-specific training is not relevant in this case because specific skills do not increase the worker's earnings.

Subsequent empirical research shows that the distinction between general and specific human capital is at best a theoretical tool, but that in reality it is difficult to find completely general or completely specific human capital. Even when it is possible to distinguish between specific and general human capital, it is not clear that the employer always pays for specific and that the worker pays for general training. Loewenstein and Spletzer (1999) analyze data from two surveys (the Employer Opportunity Pilot Project (EOPP) survey of 1982 and the National Longitudinal Survey of Youth (NLSY) of 1993), and find that most training is funded by the employer and that most part of the training is general, i.e. useful not only in the firm that pays for the training but also in other firms. The employee who is trained does not experience a wage reduction while he is being trained. Barron, Berger and Black (1999) find similar results using a data set from the Small Business Administration (SBA). Using several European datasets, Bassanini, Booth, Brunello, Paola and Leuven (2005) find that the employer pays for about two thirds of the training irrespective whether it is specific or transferable across employers.[4]

A theoretical explanation for these findings is given by Acemoglu and Pischke (1999). They argue that the employer pays for at least a part of the training in general skills if the wage structure of skilled workers is *compressed* versus the wages of unskilled workers. This means, the worker is not paid his full marginal product. Rather, the revenue which results from the skills is shared between the employer and the worker. The employer keeps a part of the rent from general skills. This outcome is reached by "labor market imperfections, which imply that trained workers do not get paid their full marginal product

[4]The datasets used are the CVTS (Continuing Vocational Training Survey), OECD data, and the European Community Household Panel.

when they change jobs, making technologically general skills de facto specific." However, if there is a positive probability that the worker quits his job for another job, part of the surplus is reaped by future employers. The future employer is unknown at the time when the investment is made and therefore cannot be asked to contribute to the investment. Therefore, the total investment in training will be less than that what results in the frictionless labor market where the worker pays for all general training himself. This gives a hint to the benefit of long-lasting employment relationships: if the worker is expected to stay a longer time at the employer she has a stronger incentive to invest in the skills of "her" worker. Labor market institution which lead to such a "compressed" wage structure, for example, are search costs or wage floors. Another setting where the wage structure is compressed is a labor market where the wage is Nash-bargained between the employer and the worker. Acemoglu and Pischke also show that the incentive of investment into skills will be lower if there is high turnover in the economy. As long as the surplus of production is shared between the employer and the employee both have a common interest in improving the productivity of the match, be it specific or general.

Another explanation for firms investing in workers' general skills is given by Kessler and Luelfesmann (2002). They show that firms have an incentive to invest in both specific and general skills when the firm and the worker split the surplus, even if the worker's outside option increases one-to-one with general skills. Their result hinges on how the worker's outside option goes into the wage bargain, namely that what both parties get if negotiations fail does not depend on the utility the worker can get in the external market. They motivate this with the 'outside option principle' (Osborne and Rubinstein, 1990, Sec. 3.12.1).

Hence, theory and evidence show that training most of the times includes general skills and that both, the employer and the employee are willing to pay for the employees training in both types of skills.

In the context of employment protection and training, several studies show that EP enhances the employees' incentives to invest in firm-specific skills (Suedekum and Ruehmann, 2003; Belot, Boone and Ours, 2007; Wasmer, 2002, 2006).

Chéron, Hairault and Langot (2008) analyze the effect of employment protection for different age groups. They determine the optimal pattern of an age-specific employment protection. They also use a life-cycle model in discrete time, but they do not consider human capital formation. Another crucial difference to the model presented here is that in their model young and old workers share the same labor market, This entails an externality in the labor market. As the firm cannot post a vacancy for a specific age group, but the return from a job filled with a young worker is larger than the return from an old worker, the labor market is too slack for young workers and to tight for old workers. Therefore a policy that influences the equilibrium can achieve efficiency gains. This is why they conclude that an age-specific employment protection would be optimal. Another important difference between the model of this chapter and theirs is that here, the distribution of human capital across the population is endogenous. In their model it is exogenous.

The focus of this exercise is on the firms' incentives to invest in the workers' skills. As the above cited evidence shows, training is mostly funded by the employer and mostly general. I want to assess the impact employment protection has on the firms' incentives to invest in the workers' skills. As the cited empirical evidence has shown, the consequences of employment protection vary depending on the age of workers affected. Therefore, I consider a life-cycle model as in Ben-Porath (1967) which allows me to investigate the effects on different age groups.

2.2 The model

In this section I outline the model which I will use to analyze the effect of employment protection on human capital formation. In the model I follow individual workers through their employment and training histories, describing the evolution of their human capital. This part of the model is similar to Ben-Porath's (1967) life-cycle model. The labor market is characterized by matching frictions. Firms post vacancies and find workers according to a matching function. The introduction of a firing tax and mandated severance payments has consequences for the wage bargain and on the firms' propensity to layoff employees after a shock. The firms choose the optimal amount of training for its employees. The analysis is restricted to the firms' behavior: it is the firm that decides about human capital investments, about hires and about layoffs. The workers have only the choice between working or not working. I do not consider issues such as the workers' motivation. In Chapter 3.1 I will show some evidence that training is mostly initiated by firms and financed by them. However, the model can easily be reformulated to analyze the workers incentives. Then, optimization decision would on the workers' side an not on the firms side.

2.2.1 Firms and workers

Consider an economy populated by a continuum of risk-neutral workers. When I refer to an individual worker I will use the subscript i. For the ease of notation I will omit the subscript whenever the context is clear. Time is discrete. Workers and firms share the same time preference parameter, β. Workers differ in their age, denoted by $t = 1, ...T$, and their human capital, h_{it}. T is the retirement age which is exogenously given and which is the same for all workers. Here, I will only consider the steady state, therefore, I will not use a time index. Instead, t refers to the worker's age cohort. Since all cohorts face the same macroeconomic environment, it makes no difference whether I consider different cohorts at one moment in time or I follow one cohort through the course of time. Here, I will use both interpretations. A worker of age $t = 1$ is at the start of his working career. Before he starts working he is endowed with some human capital, h_{i0}. This reflects the skills he learnt at school or university or in an apprenticeship. I assume that the value h_{i0} is drawn from a random distribution. A worker of age t can either be unemployed or working. When he is unemployed he looks for a job, when he is working he is attached to a firm and produces output $y_{it} = y(h_{it})$. The firms in this model can be interpreted either as one-job-one-worker firms, or they can be interpreted as large firms having constant returns to labor.[5]

A firm can create a vacancy at cost κ. The vacancies in this model are assumed to be specific to a worker type. That is, a vacancy is a means to search for a worker with a specific amount of human capital and a specific age. If the firm wants to search also for workers with a different level of human capital or a different age it has to post another vacancy and pay once more the amount of κ. However, the value κ is universal. It is the same for all vacancies and does not depend on the desired level of human capital. Denote the number of vacancies for age group t and skill group h by v_t^h, the measure of unemployed people of a specific type is u_t^h. Unemployed workers and vacancies meet according to a matching function $m(u_t^h, v_t^h)$. Labor market tightness is $\theta_t^h = \frac{v_t^h}{u_t^h}$ and is specific for each worker type, (h, t). The probability that the firm finds a worker for the vacancy is denoted by $q(\theta_t^h)$ and the probability that the worker finds a job is $\theta_t^h q(\theta_t^h)$. Once an unemployed worker and a vacancy meet they form a match. Note that the worker's prospects to find a job depend on his age and on his human capital.

2.2.2 Skill depreciation, skill investment, and layoffs

I assume that skills are only useful in the context of a particular technology. At the beginning of each period, some new production technologies are introduced which drive old technologies out of the market. Since a worker's skills are linked to a vintage of technologies, some of the worker's skills become obsolete. This happens to all workers, but the extent to which his skills devaluate is idiosyncratic to the individual worker. Consider an individual worker. The fraction of his skills which the worker can carry over to the next period, $t + 1$, is determined by the random variable $\delta_{t+1} \in [0, 1]$. It can be interpreted as a *stochastic skill discount factor*. Its distribution, F_δ, is the same for all

[5]More precisely: the firms can be interpreted as large firms where the productivity of a worker does not depend on the number of workers in the firm. What matters in this model is only the individual match. It is irrelevant how many matches accumulate to a firm as the firms behavior with respect to the worker is not influenced by the firm's size or by the other matches of the same firm.

workers, the density function is f_δ. For the ease of notation I will sometimes omit the subscript δ. I assume that $f(\delta_1) > f(\delta_0)$ whenever $\delta_1 > \delta_0$. That is, it is more likely that the worker can keep a larger share of his skills. In order to keep the worker productive, the firm can invest in the worker's skills by training him. The skill investment is denoted by I_t. The new skills can be used for production in the next period. At the end of period t the worker's human capital is $h_t + I_t$. At the time of investment the firm cannot foresee the shock of the next period. After the arrival of the shock δ_{t+1} which marks the beginning of the period $t+1$ the worker disposes of a human capital which is given by

$$h_{t+1} = \delta_{t+1}(h_t + I_t). \tag{2.1}$$

This is the amount of human capital that is available for production in period $t+1$. Equation (2.1) is the law of motion of a worker's human capital. Training comes at a cost. The cost of making a skill investment of I_t is given by the investment cost function $c(h_t, I_t)$ with $c_h < 0$ and $c_I > 0$. More training is more expensive, and the more the worker already knows, the easier it is for him to learn new things. The firm will dismiss the worker if the shock δ_{t+1} falls below a certain threshold. This threshold is the *reservation level of the skill shock*. It depends on the worker's human capital at the end of period t and is denoted by $R_t = R(h_t + I_t, t)$. Given the distribution F_δ, the ex-ante probability that a worker can keep his job is given by $1 - F_\delta(R(h_t + I_t, t))$, the probability that he is laid off is given by $F_\delta(R(h_t + I_t, t))$. A firm that lays off a worker incurs a layoff cost. The layoff cost can consist of either a firing tax, τ, or a severance payment, S, or both. A firing tax is paid to the state, i.e. it is a loss and diminishes the surplus of a job. The severance payment is a mandatory transfer from the firm to the worker. The layoff costs are imposed exogenously as a political choice. They are not intended to cure a particular inefficiency in the labor market.

If the worker is unemployed in period t he does not receive any training in that period. Therefore, his human capital in period $t+1$ is given by

$$h_{t+1} = \delta_{t+1} h_t. \tag{2.2}$$

The firm will dismiss the newly hired worker if δ_{t+1} falls below the reservation value $R_t = R(h_t, t)$.

If the firm decides not to dismiss the worker, they bargain over the wage. As soon has the wage has been set, production starts.

2.2.3 Time schedule

To fix ideas, consider a specific cohort entering the labor market. Each worker disposes of an individual endowment of human capital. The firms post vacancies for this cohort. Matching takes place. The first period starts with the arrival of the technology shocks, δ_{i1}. Those workers whose shocks fall below their reservation levels, R_{i0}, are laid off. Then, the firms and the workers bargain over the wages. Production starts. Those workers who are employed dedicate a share of their working time to training. The firms decide about the allocation of time between training and production. The unemployed workers cannot take training, but they look for a new job. Matching takes place. Eventually, the next period starts by the arrival of shocks δ_{i2}. This continues until the last period, T, is reached. In this period there is no investment because the worker will retire after T. There is no matching, either.

2.2.4 Value functions

The state of a match is characterized by the worker's human capital, h_t, and his age, t. The choice variables are investment in training, I_t, the wage, w_t, and the threshold level, R_t, which determines whether a match is maintained or severed after the arrival of the shock δ_{t+1}. Let I_t, w_t and R_t be functions of the state variables:

$$w_t = w(h_t, t) \quad I_t = I(h_t, t) \quad R_t = R(h_t, t). \tag{2.3}$$

Further below I will derive these functions $w(\cdot), I(\cdot)$ and $R(\cdot)$. Given these functions, the value of a match to the firm is also a function of the state variables. It is defined recursively as

$$J_t = \; J(h_t, t) = \; y(h_t) - w(h_t, t) - c(h_t, I_t) + \beta \mathcal{E}^J(h_t, I_t, t). \tag{2.4}$$

That is production, $y(h_t)$, minus the wage, w_t, and the training cost $c(h_t, I_t)$, plus the discounted continuation value, i.e. the value of the match to the firm next period which is denoted by $\mathcal{E}^J(h_t, I_t, t)$. It is defined as

$$\mathcal{E}^J(h_t, I_t, t) = \int_{R(h_t+I_t,t)}^{1} J\left((h_t + I_t)x, t+1\right) dF_\delta(x) \quad - F_\delta(R(h_t + I_t, t)) \, (\tau + S),$$

$$\text{for } t = 1 \ldots T-1, \text{ and} \tag{2.5}$$

$$\mathcal{E}^J(h_T, 0, T) = 0.$$

This expression takes into account that in the next period the match may be either retained or destroyed, depending on whether the skill shock falls above or below the reservation level. With a probability of $F_\delta(R_t)$, the realization of the skill shock falls below the threshold, and the firm will lay off the worker. In this case it has to pay the layoff costs. With probability $1 - F_\delta(R_t)$ the match is retained, in this case the job value of the next period is given by $J((h_t + I_t)\delta_{t+1}, t+1)$. A specific feature of the last period, T, is that there is no investment, $I_T = 0$ as the worker retires after that period. For the same reason the continuation value in T is zero. In each period the threshold value is defined as the value of the shock at which the firm is indifferent between laying off the worker and retaining the match. Therefore, the value R_t is the one where the following equation holds:

$$-\tau - S = J((h_t + I_t)R_t, t+1). \tag{2.6}$$

Solving this out for R_t yields the reservation level of the shock as a function of the state variables as we have it already expressed in (2.3).

An employed worker's present discounted utility at the age of t is given by

$$W_t = W(h_t, t) = w(h_t, t) + \beta\mathcal{E}^W(h_t, I_t, t). \tag{2.7}$$

This is the sum of the wage earned in this period, plus the discounted continuation value. The continuation value, $\mathcal{E}^W(h_t, I_t, t)$, is defined by

$$\begin{aligned}\mathcal{E}^W(h_t, I_t, t) = &\int_{R(h_t+I_t,t)}^{1} W\left((h_t + I_t)x, t+1\right) dF_\delta(x) \\ &\qquad + \int_0^{R(h_t+I_t,t)} \left[U((h_t + I_t)x, t+1) + S\right] dF_\delta(x) \\ &\qquad\qquad \text{for } t = 1 \ldots T-1 \qquad (2.8) \\ \mathcal{E}^W(h_T, 0, T) = 0, &\end{aligned}$$

taking into account that the match is retained only if next period's skill shocks realizes above its reservation level. In this case the worker again receives the utility of being employed. If the shock falls below the threshold the worker gets the utility of unemployment, $U((h_t + I_t)x, t+1)$ and receives the severance payment, S. The continuation value in T is zero because the worker retires after that period.

Worker's present discounted utility being unemployed is:

$$\begin{aligned} U_t = U(h_t, t) &= b + \beta\, \theta_t^h q(\theta_t^h) \int_{R(h_t,t)}^{1} W(h_t x, t+1) dF_\delta(x) \\ &\quad + \beta\, \theta_t^h q(\theta_t^h) \int_{0}^{R(h_t,t)} U(h_t x, t+1) dF_\delta(x) \\ &\quad + \beta\, (1 - \theta_t^h q(\theta_t^h)) \mathbb{E} U(h_t \delta, t+1) \qquad (2.9) \\ U(h_T, T) &= b \end{aligned}$$

It is composed of the period utility, b, and the expected utility next period: with probability of $\theta_t^h q(\theta_t^h)$ the worker finds a job. However, he might be laid off immediately after the shock before he starts even working. This happens if the skill shock falls below $R(h_t, t)$. With probability $1 - \theta_t^h q(\theta_t^h)$ the worker does not find a vacancy. Then he gets the utility of being unemployed. $\mathbb{E}$ denotes the unconditional expectation with respect to the skill shock δ. Note that I_t does not show up in this equation. As the unemployed worker is not attached to a firm he does not undergo any training.

2.2.5 Aggregation

For each worker type (h, t) the firm can compute the job-value $J(h, t)$. As vacancies are for a specific worker type, there is a separate labor market for each type. Due to profit maximization firms will create vacancies up to the point where the expected profit from a vacancy is equal to the cost of posting a vacancy, κ. Labor market tightness is determined by the following zero-profit condition:

$$\kappa = q(\theta_t^h) J(h, t) \qquad \forall h, t \tag{2.10}$$

Each worker faces a different labor market tightness, depending on his human capital, h, and his age, t.

2.2.6 Wage setting

In each period t, after the skill shock has arrived, but before production starts, the firm and the worker bargain over the wage, w_t. I will stick to the assumption of Nash bargaining which is standard in the labor matching literature. The firm's outside option is to break up negotiations and to lay off the worker. In this case the firm has to pay the layoff cost. The worker's outside option is to break up wage negotiations and become unemployed, encashing the severance payment. Since I do not distinguish between quits and layoffs, the worker receives a severance payment even in the case that he breaks up negotiations.

In practice, it is difficult to distinguish quits from layoffs, since the worker could sabotage the production process and this way force the firm to lay him off. The worker's bargaining power is denoted by μ. The Nash product is given by

$$w_t = \text{argmax}(W_t - U_t - S)^{\mu}(J_t + \tau + S)^{1-\mu}. \tag{2.11}$$

The firm's outside option is $-\tau - S$, i.e. to lay off the worker and to pay the firing tax and/or the severance payment. The worker's outside option is the utility from unemployment, U_t, plus the severance payment, S. Note that the firing tax and the severance payment affect the wage differently. The firing tax, τ, reduces only the firm's outside option, whereas the severance payment, S, appears twice: it diminishes the firm's outside option, but at the same time increases the worker's outside option, giving him a higher utility in case of layoff. Ljungqvist (2002) has shown that the way in which the firing tax enters the wage setting mechanism is crucial for labor market equilibrium. He does not consider a severance payment. Ljungqvist compares two cases: (1) a wage setting mechanism where the firing tax diminishes the firm's outside option, this is the case I consider here, and another case (2) where the firing tax does not show up in the Nash product. In this case, the firm's outside option is to lay off the worker without paying the firing tax. In the first case the firing tax reduces the firm's share in the wage bargain. The higher the firing tax, the lower is the firm's share. Consequently, the lower is job creation and therefore the probability to find a job. Employment is a decreasing function of the firing tax in this case. In the matching model where the firing tax does not alter the outside options, the split of the matching surplus is constant in the firing tax. Therefore, the profits are reduced very little and job creation is almost not affected. Therefore, the probability of finding employment is hardly reduced, but less workers are laid off and therefore, the total effect is an increase in employment (See figures 5 and 6 in Ljungqvist, 2002). Ljungqvist shows that, except for the wage profile, the second setting is equivalent to a setting proposed by Mortensen and Pissarides (1999), where the firm does not have to pay the firing tax if it breaks up the negotiations in the first period, but it has to pay if it breaks up negotiations in later periods. The intuition is that the firm is not obliged to pay for a layoff if there has not been a working relationship in the first place. For such a wage setting mechanism Garibaldi and Violante (2005) show that severance payments have no influence on labor market equilibrium, as long as the firm and the worker have the full flexibility to bargain the wage. Full flexibility means that they are not restricted by labor market institution like union bargained wages or minimum wages. Here, I adopt the assumption, that the firm always has to pay the firing tax. There are two reasons. I will calibrate one period to equal nine years, therefore the outcome of the bargaining will determine the wage for the next nine years. The layoff decision after the Nash-bargaining captures all possible layoffs in such a nine years period, that is not only the layoff decisions at the beginning of the working relationships but also those after four, five or six years, when EP is in force in any case. In the model, the wage bargain at the beginning determines the split of the surplus for the entire life time of the job. The expected outcomes of future bargains are taken into account in the initial bargain. If the worker is expected to receive a high wage in the future, this is taken into account in the wage bargain of the first period. An expected high future wage compensates the worker for a low wage in the present. It is plausible that in reality, the share of the surplus is not determined in the first moment when employer and employee meet, but rather after a while, when the employee has started working and when he is eligible to employment protection. Therefore, I adopt the assumption of wage bargaining, where EP is already relevant in the first wage bargain. According to Ljungqvist (2002) this is the setup where employment is reduced by the firing tax. Therefore, if I find a positive effect on employment it should be a robust result.

With this assumption the outcome of the wage bargain is

$$w_t = \mu\left(y(h_t) - c(h_t, I_t) + \beta\mathcal{E}^J(h_t, I_t, t) + \tau\right) - (1-\mu)(\beta\mathcal{E}^W(h_t, I_t, t) - U_t) + S. \quad (2.12)$$

The firing tax, τ, enters with a factor of μ, the worker's bargaining power, into the wage equation. The severance payment, S, with a factor of one. A severance payment has therefore a stronger influence on the wage setting than the firing tax.

In this equation also the firm's investment I_t appears, the firm and the worker anticipate the firm's decision on the training investment in the same period and they share the investment cost. The worker bears a share of μ, the firm a share of $1-\mu$. This decision about I_t itself does not depend on the wage. Notwithstanding this bargain, the firm must offer a wage to the worker which makes the worker at least indifferent between the outside option and working, i.e. the lowest acceptable wage w_t^{min} fulfills

$$w_t^{min} + \beta\mathcal{E}^W(h_t, I_t, t) = U_t + S. \quad (2.13)$$

Appendix 2.A shows that in fact this wage w_t^{min} will never be paid because

$$w_t^{min} > w_t \Leftrightarrow J_t < -\tau - S, \quad (2.14)$$

i.e. whenever the "minimum" wage w_t^{min} is higher than the bargained wage w_t, the firm is better off if it lays off the worker. Whenever $J_t > -\tau - S$, i.e. it is profitable to keep the worker, the worker is better of when he receives the bargained wage w_t. Therefore, always the bargained wage will be paid.

2.2.7 The human capital production function and the cost of training

The higher the worker's initial value of human capital, the easier it is to teach him new skills. On the other hand, it is more costly to train the worker if he has a high level of human capital because the opportunity cost of training is higher in this case.

Like Ben-Porath (1967), I assume that the creation of human capital follows a human capital production function,

$$I = \tilde{I}(D, h, s).$$

Inputs in human capital production are the initial value of worker's human capital, h, the share of time which the worker dedicates to training, $s \in [0, 1]$, and some goods and services which are purchased on the market, denoted by D, like books or the work of teachers. The output of the function are the new skills. The newly created skills constitute an investment and are therefore denoted by I. Training the worker is costly. The cost of training consist of the *direct cost* (spending on books, tuition fees) and *indirect cost*, forgone production. Total costs are given by $C = y(h_t) \cdot s + P \cdot D$, where P is the price of input goods and services.

The worker's current level of human capital is inherited from the past and cannot be influenced by the firm, but the firm can decide on how much of his time the worker dedicates to production and how much to training activities. Of course, the maximum share of time which the worker can dedicate to training is limited to one. Unlimited are, in principle, the other inputs which are purchased on the market. If a worker dedicates his full working time to training, skill investment can still be increased by purchasing more expensive learning material or by engaging a better and more expensive teacher. However, the returns to these are decreasing if the other inputs are fixed. The firm has to decide on the optimal ratio of time and learning material. For a desired level of human capital investment, I_t, the firm chooses optimally the number of training units, D, and the share of time the worker may dedicate to learning, s, such that the marginal rate of substitution of both factors is equal to the ratio of marginal costs:

$$\frac{\frac{dI(D,h,s)}{ds}}{\frac{dI(D,h,s)}{dD}} = \frac{y(h_t)}{P} \quad \text{if} \quad s \in [0,1], \quad > \frac{y(h_t)}{P} \quad \text{if} \quad s = 1. \tag{2.15}$$

This condition and the human capital production function (2.2.7) let me determine the optimal relationship between time to learning, s, and material, D. This results in functions $s^*(h, I)$ and $D^*(h, I)$ which determine the optimal time share and the optimal amount of services and goods, given a desired level of training and the initial value of human capital.

Since the worker's time is bounded from above by 1, it is not possible to increase this input beyond the value of 1. Denote the value of investment, where the full time is used for learning by $\bar{I}$. This reasoning and the rule (2.15), lead to the investment cost function

$$\hat{c}(h, I) = \begin{cases} y(h_t) \cdot s^*(h, I) + P \cdot D^*(h, I) & \text{for } I < \bar{I} \\ y(h_t) + P \cdot D^*(h_t, I) & \text{for } I \geq \bar{I}. \end{cases} \tag{2.16}$$

Given this cost function, the firm can choose the optimal level of investment. The cost of investment accrues this period, but the revenue can only be reaped in subsequent periods as long as the match is not destroyed. Nash bargaining makes the firm and the worker split the cost of investment as well as the additional surplus. If the firm invests in the worker's skills in this period it will have to pay a higher wage to the worker later on. The firm determines the optimal level of investment by equating marginal cost, obtained by deriving (2.16), to marginal returns. Marginal returns are obtained by applying Leibniz rule to (2.4) and (2.5). Thus, the optimal decision is characterized by

$$\frac{dc(h_t, I)}{dI} = \beta \left[\int_R^1 \frac{dJ((h_t + I)x, t)}{dI} f_\delta(x) dx - (J((h_t + I)x, t) + \tau + S) f_\delta(R) \frac{dR}{dI} \right]. \tag{2.17}$$

Write this in short as

$$c_I(h, I) = \beta \mathcal{E}_I(h, I, t). \tag{2.18}$$

The firm will invest the amount of I_t in the worker's training as long as the cost of training is covered by the future profits of employment, i.e. if

$$c(h, I) \leq \beta \mathcal{E}(h, I, t). \tag{2.19}$$

The solution is a function of the state variable, h_t, yielding the optimal amount of investment:

$$I_t^* = I(h_t, t). \tag{2.20}$$

Plugging this function into (2.16), the cost of investment can be expressed as a function of the state variables

$$c(h_t, t) = \hat{c}(h_t, I(h_t, t)). \tag{2.21}$$

In the same way the wage can be expresses as a function of only the state variables h_t and t:

$$w_t = w(h_t, t) \tag{2.22}$$

Using the definition of the job value in (2.4) and plugging in the wage equation (2.12), the continuation value of the job can be expressed as

$$\begin{aligned}\mathcal{E}^J(h_t, I_t, t) = \int_{R(h_t+I_t,t)}^{1} & (1-\mu)\left[y(h_{t+1}) - \hat{c}(h_{t+1}) + \beta\left(\hat{\mathcal{E}}^J(h_{t+1}, t+1)\right.\right. \\ & \left.\left. +\hat{\mathcal{E}}^W(h_{t+1}, t+1) - U(h_{t+1})\right)\right] \quad dF_\delta(x) - F_\delta(R(h_t,t))\,\tau \ - S, \qquad (2.23) \\ & \qquad\qquad\qquad\qquad \text{for } t = 1 \ldots T-1, \\ & \text{where} \quad h_{t+1} = (h_t + I_t)x \\ & \text{and} \quad\ \ \hat{\mathcal{E}}^i(h_{t+1}, t+1) = \mathcal{E}^i(h_{t+1}, I(h_{t+1}, t+1), t+1); \quad i = J, W.\end{aligned}$$

This equation shows that the severance payment enters with a factor of one, i.e. the continuation value of the job is diminished by the amount of the severance payment. The reason for this is that the severance payment is not only paid to the worker in the case of layoff, but the firm is forced to raise the worker's present discounted utility in such a way that it matches at least his outside option, increased by S.

2.2.8 Functional forms

I assume the following functional forms: the production function of goods is given by

$$y(h) = Zh^\alpha, \qquad \alpha \in [0,1]. \tag{2.24}$$

The *human capital production function* is in the style of Ben-Porath (1967) and given by:

$$I = G(sh)^\phi D^\psi, \qquad \phi, \psi > 0 \wedge \phi + \psi \leq 1, \tag{2.25}$$

where G, ϕ and ψ are parameters. The *matching function* is assumed to be Cobb-Douglas and given by:

$$m = Au^\gamma v^{1-\gamma}, \tag{2.26}$$

where A is the matching efficiency and γ the elasticity of the matching function with respect to unemployment.

As for the distribution of the starting value of human capital I assume a log normal distribution. The density function of the stochastic depreciation factor of skills is given by

$$f_\delta(\delta) = \lambda\delta^{\lambda-1}\mathbb{I}_{(0,1)}(\delta), \tag{2.27}$$

where $\lambda > 0$ is a parameter. The expectation of δ is the average depreciation factor of skills and equals $\mathbb{E}[\delta] = \frac{\lambda}{1+\lambda}$. $\mathbb{I}_{(0,1)}(\delta)$ is the indicator function, taking the value of unity if δ is between zero and one. This density function depends only on one parameter, and its realization is always between zero and one, i.e. the worker can always keep a fraction of his skills which is smaller than one. For $\lambda \to 1$ the distribution conforms to the uniform distribution. For $\lambda \to \infty, \mathbb{E}[\delta] \to 1$. As long as the parameter λ is larger than 1, the expectation is above 0.5, and the density left-schewed, i.e. it is *more likely* that the worker can keep a *larger share* of his skills.

The investment cost function is given by

$$c(h, I) = \begin{cases} \left[\frac{Z^{\phi}}{G} + P^{\psi} I h^{-(1-\alpha)\phi}\right]^{\frac{1}{\phi+\psi}} \left[\left(\frac{\phi}{\psi}\right)^{\frac{\phi}{\phi+\psi}} + \left(\frac{\psi}{\phi}\right)^{\frac{\psi}{\phi+\psi}}\right] & \text{for } I \leq \bar{I} \\ Z h^{\alpha} + P\left(\frac{I}{G}\right)^{1/\psi} h^{-\frac{\phi}{\psi}} & \text{for } I \geq \bar{I}, \end{cases} \tag{2.28}$$

$$\text{where } \bar{I} = I \leq G h^{\phi+\alpha\psi} \left(\frac{Z\psi}{P\phi}\right)^{\psi} G.$$

This function has been derived by plugging (2.24) and (2.25) into (2.16). This investment functions satisfies the assumptions $c_h < 0$, $c_I > 0$, and $c_{II} > 0$. Additionally we have that $c_{hI} < 0$.

2.2.9 Forces at work

All relevant decisions in this model are made by the firms: they decide about job creation, about the investment in human capital, and they take the decision whether to lay off a worker. All these decisions are based on the worker's human capital and his age. A worker's fate is therefore closely linked to the evolution of his human capital. At the beginning of the first period, all workers get a skill endowment which is drawn from a random distribution. The worker faces a labor market tightness which is determined by the number of vacancies that firms create for his specific level of human capital. The firms create more vacancies for workers who have a higher level of human capital. Therefore, the labor market tightness for each individual worker is different. So is the worker's job-finding-probability. All workers, those who are matched to a firm, and those who are not, are subject to the skill shock. Each period, the distribution is altered by the firm's investment decision and by the skill shocks. Thus, the distribution of human capital evolves endogenously, and is marked by the interactions of skill shocks and the firms' decisions about training the workers. The aggregate variables in the model like the unemployment rate and the average wage are driven by these events on the micro level. The outcome is a distribution of human capital and, closely linked, the distribution of the wages. Figure (2.10) in Appendix 2.C shows the evolution of the wage distribution in the course of the five periods of the life cycle and compares it to the empirical distribution of earnings, taken from the Current Population Survey.

The layoff costs bias the firm's decision towards maintaining the match. A firm will lay off the worker if the realization of the productivity shock falls below the value of R

for which equation (2.6) is fulfilled. Plugging the wage equation (2.12) into the definition of the job value (2.4) and this into (2.6) translates that condition to

$$-\tau - S = (1-\mu)\left[y(h_t) - c(h_t, I_t) + \beta\mathcal{E}_t^J + \beta\mathcal{E}_t^W - U_t\right] - S. \tag{2.29}$$

S is on both sides and drops out. Therefore it does not influence the layoff decision. This is the first result of this chapter: A severance payment does not influence the layoff decision under the wage setting mechanism assumed here. However, a severance payment will always lower the profits a firm can earn from a job and therefore repress vacancy creation in the first place.

A firing tax does have an influence on the layoff decision. A filled job is for the firm a kind of option on the future: In case the worker is unproductive today he might become productive tomorrow. The firm weighs the cost of keeping the worker against the probability that he becomes productive again. On the other hand, EP reduces the profits which the firm can earn from the job. This is especially true for a severance payment. Equation 2.23 shows that a severance payment reduces the job value by a factor of one.

Let's have a look at the firm's decision on how much to invest in its employee. The continuation value of the job, defined in equation (2.5) is increased by additional investment:

$$\begin{aligned}\frac{d\mathcal{E}^J(h_t, I_t, t)}{dI} &= \int_{R((h_t+I)x)}^{1} \frac{dJ((h_t+I)x, t+1)}{dI} f(x)dx \\ &\quad - f(R(h_t+I))(\tau + S + J((h+I)R, t+1))\frac{dR(h_t+I)}{dI} > 0\end{aligned} \tag{2.30}$$

This derivative shows the effect of investment on the continuation value of the job. The first part (the integral of the derivative of the job value) captures the positive effect of additional human capital on future production. This part is unambiguously positive because the firm's share of production is kept constant, and future production is increasing in human capital. The second part captures the movement of the reservation level of the skill shock. If the worker receives a lot of training (I is high), the worker has more human capital (higher $h_t + I$) and a relatively worse shock is needed in order to make the match unprofitable: the reservation level of the shock, R, is decreased ($\frac{dR(h_t+I)}{dI} < 0$). This leads to an increase in the probability that the job is maintained : $1 - F(R)$ increases. The increase in probability is measured by $f(R)\frac{dR}{dI}$. In these events the firm does not have to pay the layoff cost but gets the job value, therefore the measure is multiplied by $\tau + S + J(\cdot)$.

The introduction of a firing tax reduces the firm's outside option in the wage bargain: it becomes negative. The severance payment has the same effect, but additionally it increases the worker's outside option. This does not happen with a firing tax because a firing tax is paid to the state. Therefore, the worker's position in the wage bargaining is strengthened much more with a severance payment than with a firing tax. A firing tax has two effects: (1) it weakens the firm's position in the wage bargain so that the worker earns a higher wage, (2) it reduces the reservation level of the skill shock, i.e. the firm is more tolerant with respect to skill losses of the worker. This means that the worker will - on average - stay a longer time in the firm. This gives the firm more time to reap the fruits of investment in the worker. On the other hand, the firm will have to pay a higher wage to the worker and the firm's share of production decreases. Consider the derivative of investment with respect to the firing tax obtained by totally differentiating (2.17):

$$\frac{dI}{d\tau} = \frac{\beta \mathcal{E}^J_{I\tau}}{c_{II} - \beta \mathcal{E}^J_{II}}, \tag{2.31}$$

where $\mathcal{E}^J = \mathcal{E}^J(h_t, I, t)$, defined as in (2.5). The sign of this derivative is indetermined. We have $c_{II} > 0$ by the assumptions of the investment cost function. But the signs of $\mathcal{E}_{I\tau}$ and $\mathcal{E}_{II}$ depend on the individual values of human capital and on the functional forms. Consider $\mathcal{E}^J_{I\tau}$, the cross-derivative of the continuation value of the job with respect to investment and the firing tax:

$$\begin{aligned}\frac{d^2\mathcal{E}^J_t}{d\tau dI} &= \int_{R_t}^1 \frac{d^2 J_{t+1}}{d\tau dI} f(x)dx - f(R_t)(\tau + S)\frac{d^2 R_t}{d\tau dI} - f(R_t)\left(1 + \frac{dJ_{t+1}}{d\tau}\right)\frac{dR_t}{dI} \\ &- \left(f'(R_t)\frac{dJ_{t+1}}{dI} + \left[(f'(R_t) + f(R_t))J((h_t + I)R_t, t+1) + f'(R_t)(\tau + S)\right]\frac{dR_t}{dI}\right)\underset{\ominus}{\frac{dR_t}{d\tau}}.\end{aligned} \tag{2.32}$$

The sign of the derivative depends on how the firing tax influences the return of an additional unit of investment. The first term in the upper line of equation (2.32) measures the change of the impact of an additional unit of investment on the job-value when the firing tax is increased by a marginal unit, keeping the reservation productivity constant. This term is negative, because when a firing tax is introduced (or increased), the firm will keep a smaller part of the additional investment. It loses part of the return to investment in form of the firing tax. The second term captures the change of the reservation shock. The question is, by how much an increment in investment reduces the reservation level: is this move smaller or larger when there is a firing tax? This is not clearly determined. The last term of the upper line incorporates the decrease in the job value which is directly due the firing tax. It is multiplied by the measure of events on which the match is maintained, $f(R)$. The second line captures the effect that is generated by shifting the reservation productivity to the left. This leads to an increase of the value. The firm gets additionally the return that accrues in those events where the match is not destroyed, but would have been if the firing tax had not been introduced. The first term in parentheses is positive, as the job value increases if investment is increased and the rest is unchanged. The second term in parentheses is negative as $\frac{dR}{dI} < 0$, and the term in square brackets is positive.

The second derivative of the continuation value with respect to investment, $\mathcal{E}^J_{II}$, is given by

$$\begin{aligned}\frac{d^2\mathcal{E}^J_t}{dI^2} = &\int_{R_t}^{1} \frac{d^2 J_{t+1}}{dI^2} f(x)dx - \left[2f(R_t)\frac{dJ_{t+1}}{dI} + f'(R_t)\frac{dR_t}{dI}(\tau + S + J_{t+1})\right]\frac{dR_t}{dI} \\ &- f(R_t)[J_{t+1} + \tau + S]\frac{d^2 R_t}{dI^2}.\end{aligned} \tag{2.33}$$

The first part of this equation is negative due to decreasing returns to investment. The signs of the other two parts is indetermined as $\frac{dR}{dI} < 0$ and the sign of $\frac{d^2R}{dI^2}$ is indetermined.

An increase in the firing tax leads to a reduction in the firm's profit in the case of layoff. However, the less likely a layoff is and the further it is delayed into the future, the less will firm's profit be affected. Therefore, a firm that employs a worker who has a high level of human capital and who is therefore very unlikely to be laid off will hardly notice the difference. On the other hand, a firm that employs a worker with a low level of human capital will experience a strong reduction of expected profits. Since profit opportunities are reduced, the firm will create less vacancies which leads to an increase of the unemployment rate. Therefore, the effect of the firing tax depends on the initial level of the worker's human capital, on his age and on the parameterizations.

The incentive to invest in the worker's human capital works via the expectation to keep the worker a longer time. A severance payment does not change the reservation productivity and has therefore no direct effect on training:

$$\frac{d\mathcal{E}}{dS} = 1 \Rightarrow \frac{d^2\mathcal{E}}{dIdS} = 0. \tag{2.34}$$

As the effect of the firing tax on training is not clear from the algebraic expressions, I simulate the model for different levels of a firing tax. I simulate the model also for different levels of the severance payment in order to compare the impact of both policy instruments on employment.

Table 2.1: Calibrated parameters

Production function		
Scale parameter of production function	Z	1.871
Elasticity of production function	α	0.723
Human Capital		
Starting value of HK (population mean)	$\mathbb{E}[h_0]$	2
Starting value of HK (variance)	$\mathrm{Var}[h_0]$	1.5
Skill discount factor (expectation)	$\mathbb{E}[\delta]$	0.63
Scale parameter of investment function	G	7.031
Elasticity of human capital	ϕ	0.81
Elasticity of goods in HK production	ψ	0.17
Price of goods and services for training	P	0.0028
Labor Market		
Unemployment utility	b	0.25
Vacancy cost	κ	0.444
Matching efficiency	A	0.574
Elasticity of matching function	γ	0.7
Worker's bargaining power	μ	0.7
General		
Real interest rate p. a.	$\frac{1-\beta}{\beta}$	0.04
Discount factor	β	0.703
Number of years per period		09

One period corresponds to nine years. The skill discount factor is the expectation of the random variable δ with distribution F_δ. $E[h_0]$ ist the average of the workers human capital endowments.

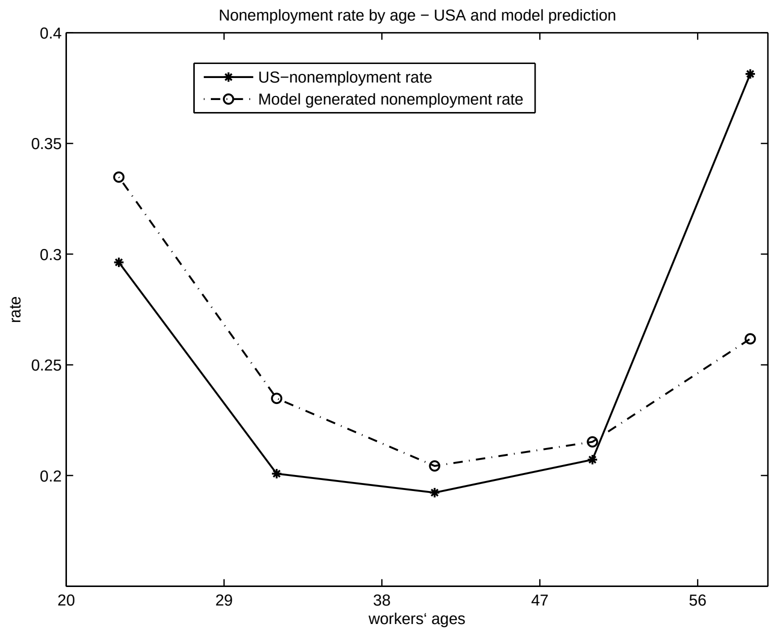
2.3 Simulation

2.3.1 Calibration

In the calibration I want to cover a typical working life, i.e. from the 20th until the 65th birthday. I divide this 45-years-span into five periods that represent different segments of a worker's life. I work with a small number of periods in order not to complicate the computation of the solution unnecessarily and to achieve that it can be solved easily. A minimum number of periods is necessary in order to generate the desired dynamics of job finding and layoffs during a life-cycle. Thus, I can generate the unemployment rates for different age groups. The five periods in the model represent the five periods of a worker's life from 20-28, 29-37, 38-46, 47-55, 56-65 years. One period in the model corresponds to nine years in real life.

I start from a benchmark calibration without employment protection. Then, I intro-

Figure 2.1: Calibration: nonemployment rate

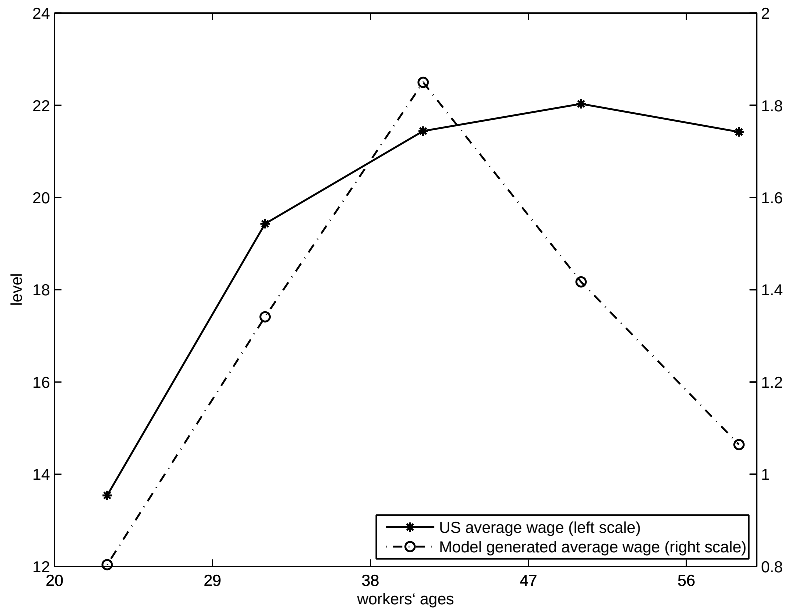


Nonemployment rate in the USA and from the simulation for five different age groups. The US-nonemployment rate is the average of 2006 as calculated from the Current Population Survey. The simulated nonemployment rate comes from the benchmark simulation without employment protection.

duce employment protection in the economy and examine the changes in human capital accumulation and the unemployment rate. For the benchmark, I choose the United States, because they have the lowest level of employment protection of all OECD-countries (OECD, 2004). Some values of the calibration are taken from the literature. Other values I determine by pinning down some moments of US labor market data: the nonemployment rate and the aggregate wage. The parameters of the calibration are reported in Table 2.1.

The elasticity of the matching function has been calibrated by many studies before, therefore I can take the value from the literature. I rely on Shimer (2005) and set it to 0.7. I set the worker's bargaining power to the same value, thus fulfilling the Hosios (1990) condition. This is in the upper range of what Petrongolo and Pissarides (2001) suggest. The unemployment utility is constant in the model. An unemployed worker's replacement ratio is determined by dividing the unemployment utility by the worker's wage that he earned before becoming unemployed. Therefore, the replacement ratio is individual to each worker, and it can only be calculated for those individuals who have been laid off. After I have simulated the model and determined the employment histories of all workers' I can calculate the replacement ratios. I choose a value of the unemployment utility

Figure 2.2: Calibration: average wage



Average wage in the US and from the simulation for five different age groups. The average wage is calculated from the Current Population Survey, using all twelve months of 2006. The wage is adjusted for topcoding and overtime pay, tips and commission as suggested by Schmitt (2003). The simulated wage comes from the benchmark simulation without employment protection.

that predicts a median replacement ratio of approximately 0.73. This is in line with the estimation of the replacement ratio in Petrongolo and Pissarides (2001) and a bit above the replacement ratio which is prescribed by the German law to 0.6.[6] For the discount factor I assume a real interest rate of 0.04 p.a. This assumption yields a per-period discount factor of 0.7026. The parameters of the log-normal distribution which determines the workers' skill endowments I choose in order to match the empirical wage distribution of the young workers, depicted in panel a of Figure 2.10 in Appendix 2.C.

Now, I am left with nine parameters: the average value of the skill discount factor, $\mathbb{E}[\delta]$, the scale parameters of the human capital production function, G, the elasticity of human capital production with respect to the initial level of human capital, ϕ, the elasticity of this function with respect to goods and services, ψ, the cost of goods and services used in human capital production, P, the scale parameter of the production function, Z, the elasticity of human capital in the production function, α, the efficiency parameter of the matching function, A, and the vacancy posting cost, κ. As it is difficult

[6] In Germany, a worker who is unemployed receives unemployment compensation of two thirds of his last wage.

to find estimates for these parameters, I calibrate them trying to match labor market data from the US economy to the predictions by the model. The labor market variables I use are the nonemployment rate and the average wage.[7] I consider the values of both these variables for the five different age groups separately. Thus, I have ten data points, which I can match to model-generated predictions. I run an algorithm that simulates the model for different combinations of parameter values and figures out those combinations that match the data as close as possible. As a data source I use the Current Population Survey (CPS). I use data from all twelve sequels of the survey in 2006 and calculate the unemployment rates and average wages for the age groups. Figure 2.1 and Figure 2.2 plot the model-generated nonemployment rates and averages wages against those from the CPS.

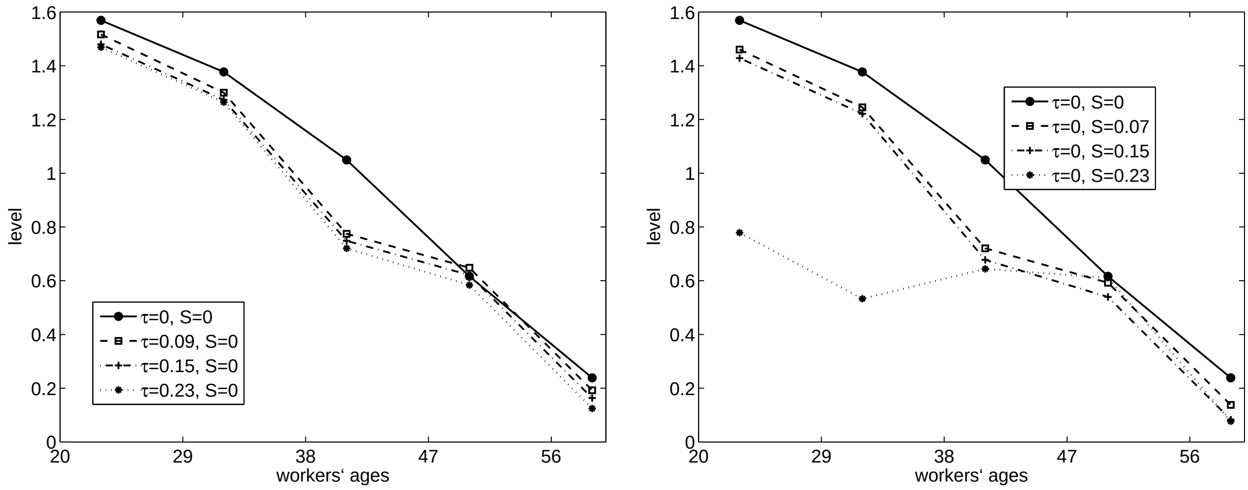
2.4 Results

I simulate the model with different levels of both types of employment protection: a firing tax and a severance payment. For each case I simulate 10 economies each of which consists of 10 000 workers, then I compute the averages of these 10 simulated economies. First, I simulate the model with four different levels of a firing tax, keeping the severance payment at zero. Then, I simulate the economy with four different values of a severance payment, keeping the firing tax at zero. I choose the same values for both types of employment protection in order to compare the impact of both policy instruments. The four different levels of employment protection are 0, 0.07, 0.15 and 0.23. The figures on the following pages depict the results of the simulation and show the evolution of aggregate wages, nonemployment and human capital investments in the economy under the different policy regimes.

Figure 2.3 shows the average of the job value, taken over all matches in the economy of the corresponding age group. In the calibration without employment protection the job value is just above 1.5 for the young worker of age 20. This means that a firm that employs a worker who is at the age of 20 can expect total of present discounted profits of 1.5. In the case of a firing tax of 0.23 the job value is reduced to 0.8. This means that in the case of layoff the firm will have to pay an amount that corresponds to a quarter of the profits it had expected at the beginning of the match. The older a worker gets the lower is the value of expected profits as there are less periods that the worker can be producing. Therefore, it is more attractive for firms to offer jobs to young workers. The figure shows that the introduction of a firing tax or a severance payment reduces the job value for all ages. As long as the firing tax does not exceed a certain threshold the effect is small.

[7] As the model does not distinguish between unemployment and nonemployment, the unemployment rate in the model corresponds to the nonemployment rate in the data.

Figure 2.3: Average job value



(a) Firing Tax (b) Severance Payment

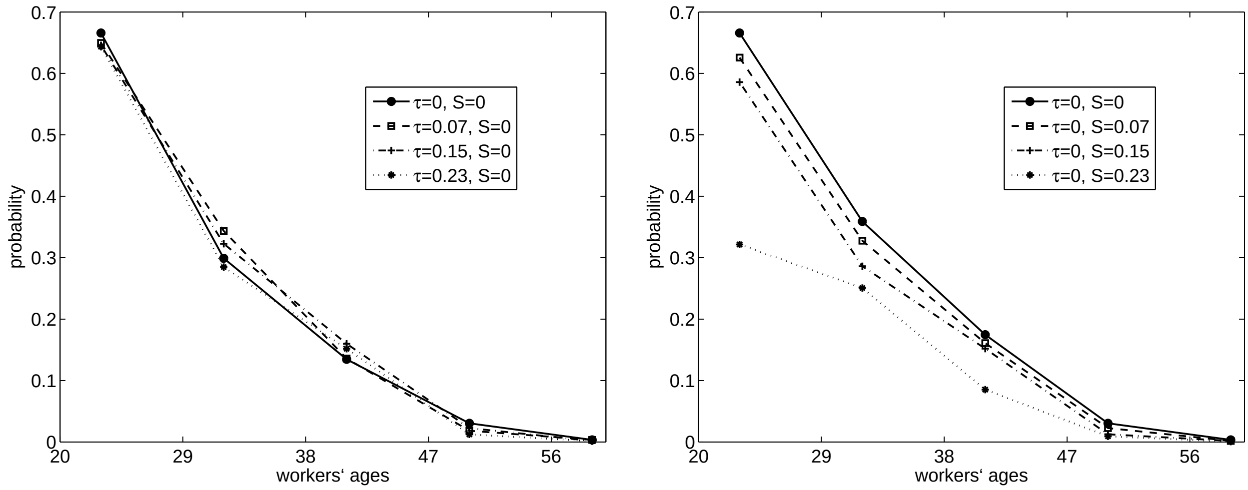
Average of the net present value of all jobs in the economy. The different graphs refer to different levels of employment protection.

For middle-aged workers the reduction of the job value is a bit stronger. A severance payment reduces the job value by more than a firing tax of the same size. The effect of the severance payment is stronger because in addition to lowering profits the severance payment improves the worker's position in the wage bargain so that the worker gets a higher share of production whereas the firing tax does not. A firing tax of 0.23 reduces the expected profit drastically. Apparently, the reaction of the job value to employment protection is nonlinear. For a severance payment below a certain threshold the job value is reduced only a little, above the threshold the reduction of the job value is very strong. The reduction of the job-value shows that a firm would generally object the introduction of employment protection into the wage contracts, because it reduces expected profits.

The reduction of the job value leads to less vacancy creation. The job finding probability is depicted in Figure 2.4. For older workers it is more difficult to find a job. Employment protection does affect these probabilities, however the effects are small, only with a severance payment of 0.23 the job finding rate is reduced considerably. For a level of a firing tax larger than 0.25 the the job finding rate (not depicted here) is also depressed strongly for all age groups.

Figure 2.5 shows that a firing tax achieves its objective: Layoffs are clearly reduced, especially for the group of old workers. For a severance payment the picture is different: As discussed in Section 2.2.9, a severance payment does not influence the layoff decision directly. However, there is an indirect effect: As it reduces vacancy creation only workers with a relatively high endowment of human capital find a job. These workers are

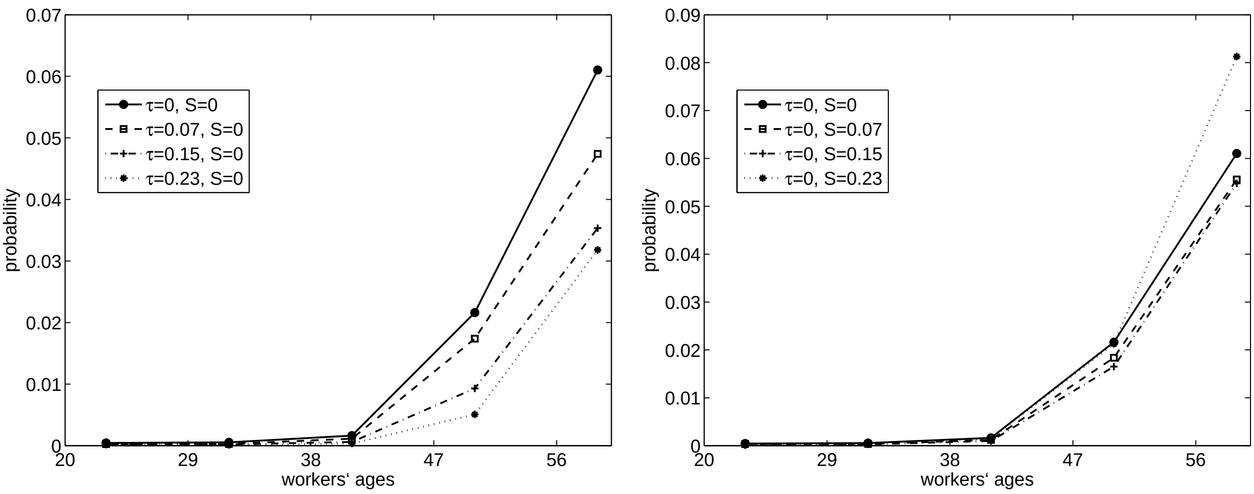
Figure 2.4: Job finding probability



(a) Firing Tax (b) Severance Payment

Average job finding probability. The average is taken for all workers who are not employed in the corresponding period.

Figure 2.5: Average layoff probability



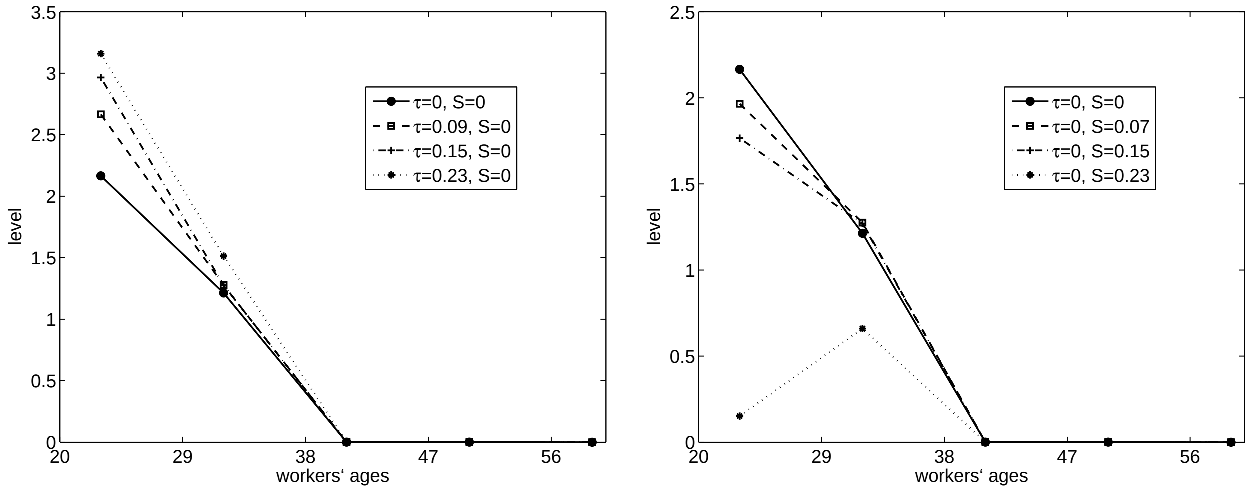
(a) Firing Tax (b) Severance Payment

Average probability of layoff. The average is taken for all workers who are not employed in the corresponding period.

highly productive and therefore less likely to be fired. The average probability of layoff is therefore reduced. An exception is the very high severance payment.

One reason for the reduction of layoffs is that workers are more productive due to increased human capital investments. Figure 2.6 shows the average of human capital

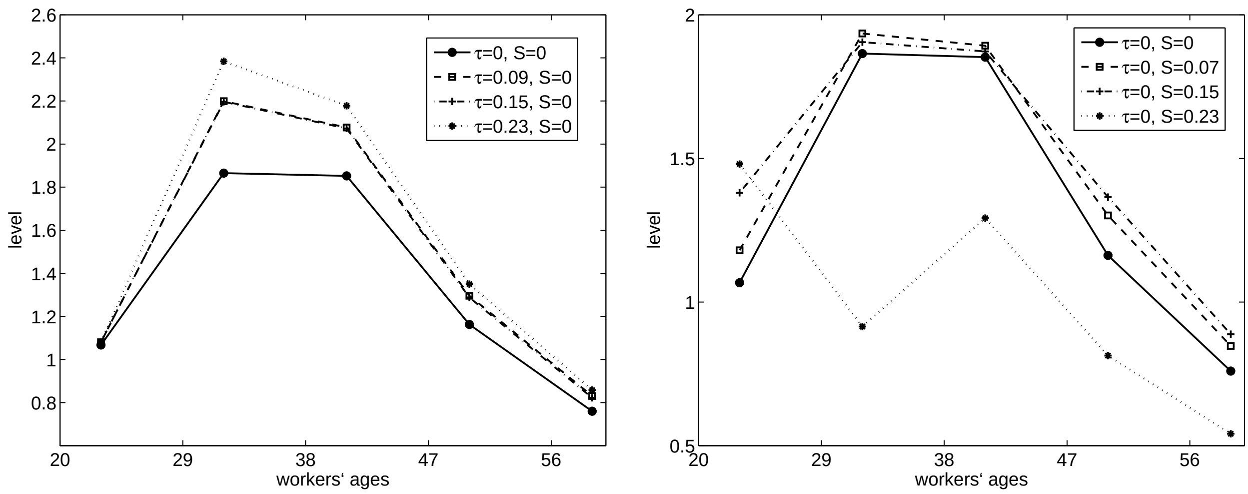
Figure 2.6: Human capital investments



(a) Firing Tax (b) Severance Payment

Intensity of human capital investments. Averages over all employed workers in the corresponding age groups

Figure 2.7: Average human capital



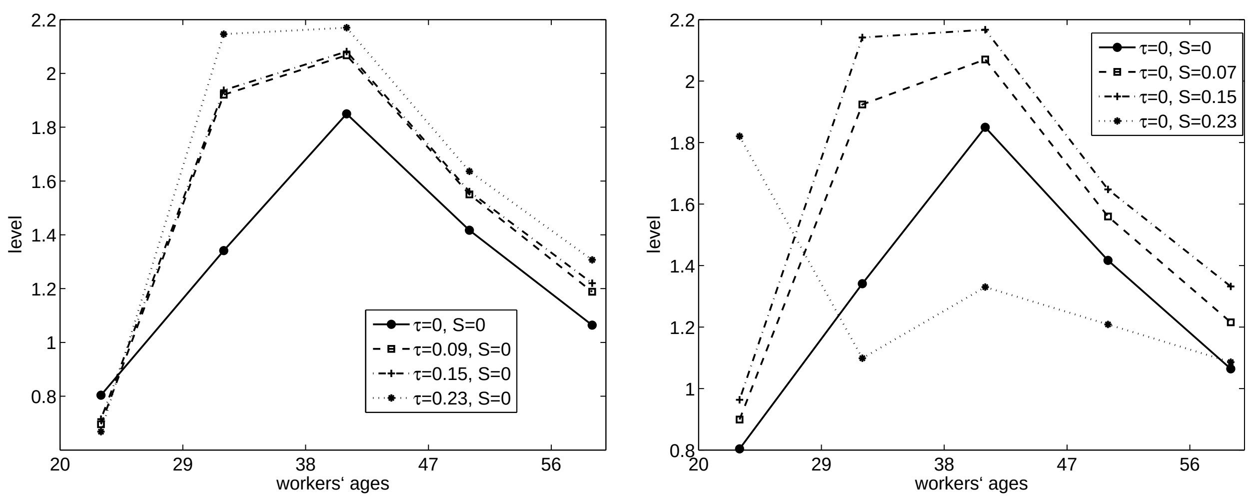
(a) Firing Tax (b) Severance Payment

Average human capital levels of all employed people.

investments in the economy. A moderate level of a firing tax indeed increases human capital investments. In Section 2.2.9 the forces that lead to this outcome have been discussed: For a moderate level of employment protection firms avoid paying the layoff costs by investing in the worker's human capital. However, training increases only for young workers. For old workers the training effort does not increase at all. A very high severance payment increases the bargaining position of the workers in the economy to such an extent that the surplus that remains to be shared between the firm and the worker is so small that it can not compensate for the cost of investment, in other words condition (2.19) is not fulfilled. Therefore, in that case many workers receive no investment at all. For the younger workers, although there is no direct effect of a severance payment on training, there is an indirect effect: As job creation is reduced, the workers' outside options are depressed which worsens the workers position in the wage bargain.

The different training efforts are reflected in human capital levels. Figure 2.7 shows the evolution of the average human capital level where the average is taken over all employed people in the economy. The differences result from the different training levels for the individual employees and from the differences in employment. This becomes very clear from the graph of the case with a very high severance payment in panel b). As the severance payment is so high only those individuals with a large skill endowment get a job in the first place. Therefore, the average level of human capital is higher in the first period. However, as they is very little training in that economy, the workers' human capital deteriorates and is lower than in the other cases.

Figure 2.8: Average wage

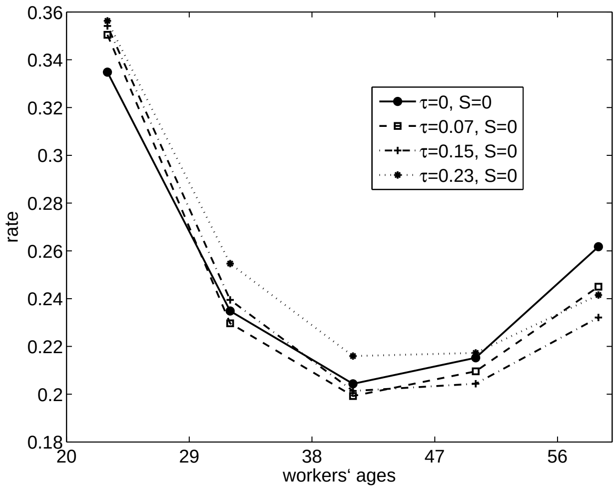


(a) Firing Tax (b) Severance Payment

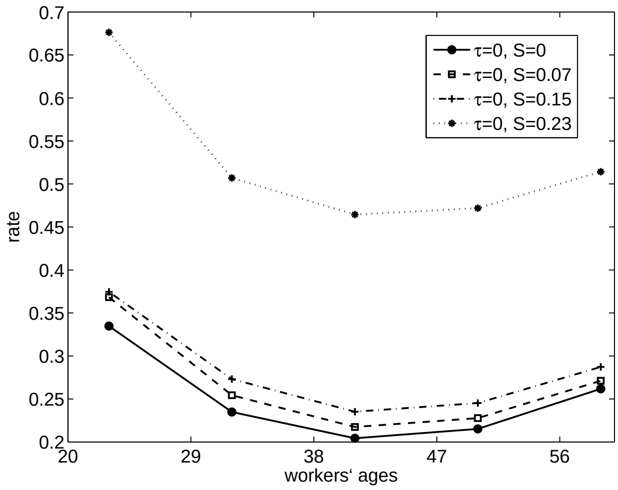
Average wage. The average is taken over all employed people in the simulated economies.

Figure 2.8 shows the average wage in the economy. High human capital translates into higher wage payments. For young workers, the introduction of a firing tax or a severance payment reduces the average wage, for all other age groups the wage is increased. This is partly due to the higher level of human capital and partly due to the worsening of the firm's bargaining position. As expected, a severance payment always leads to a wage

Figure 2.9: Nonemployment rate



(a) Firing Tax



(b) Severance Payment

Nonemployment Rate. Average over the simulated economies.

increase. The policy function of the wage are depicted in Figure 2.11 in Appendix 2.C. In the first period, workers with a very low level of human capital earn a negative wage. This can be interpreted as the workers paying for their training.

Figure 2.9 depicts the nonemployment rates for the different levels of employment protection. Without employment protection there is a distinct increase in nonemployment for workers above the age of 47. With employment protection, this increase in the nonemployment rate is mitigated. The firing tax and the severance payment inhibit layoffs, as we have seen from Figure 2.5, and translates into a lower nonemployment rate for workers. Generally, employment protection increases the nonemployment rate. However, for older workers, in fact, we can attest a positive effect on employment. This positive effect on employment is higher for a firing tax than for a severance payment. It is interesting to look at the nonemployment rate and to compare it to the findings of other studies. Here, we have adopted a wage setting mechanism that leads to a reduction of employment in a standard matching model without human capital accumulation (Ljungqvist, 2002). However, here, we see that even with that wage setting rule it can lead to an increase in employment of old workers compared to the economy without employment protection. This shows that is relevant to consider the effects of employment protection on different age groups separately.

2.5 Implications

In this chapter I have developed a model that combines matching in the labor market with human capital formation over the workers' life cycles. In this setting I have introduced employment protection and analyzed the consequences on the firms' incentives to invest in the training of their employees. The simulation has shown that a moderate level of a firing tax increases investment in human capital, but a large firing tax is detrimental to vacancy creation and training. Workers benefit from a moderate firing tax in two ways: They get more training when they are young, and they benefit from secure employment when they are old. The positive effect of a firing tax on training arises because firms try to avoid paying the firing tax by keeping the workers instead of laying them off. However, when the firing tax is too high, these positive effects are not observed.

A mandated severance payment does not have these beneficial effects. It leads to a rise in the present value of the worker's wage payments exactly of the size of the severance payment. This is due to the assumed wage setting mechanism, where the wage is determined by Nash-bargaining and the severance payment increases a worker's outside option. Therefore, it has no effect on the layoff decision, nor does it increase the firms' incentives to invest in the workers' human capital. Both policy instruments reduce profits and vacancy creation, and young workers face more difficulties to find a job.

A similar mechanism works in a model proposed recently by Chéron et al. (2008). In their model they analyze the effect of employment protection on employment of workers of different age. In that model the firm cannot observe the worker's age beforehand. Therefore, in that model an intergenerational externality arises: Many unemployed old workers decrease the job-finding probability of young workers. Due to that assumption they get an optimal employment protection that is hump-shaped: increasing in age for workers who are younger than a certain threshold age and decreasing in age for workers who are older than that threshold. In the model of this chapter this does not occur because old and young workers are searching in different labor markets. Questions relating to efficiency has not been considered in this chapter. Therefore, I don't take a stand whether it would be efficient to have age-dependent employment protection.

This study implies that given a moderate level of employment protection in the economy, a reduction of employment protection will tend to discourage the firms's training efforts. What do the findings imply for economic policy? In Germany, for example, the laws in force cannot be directly translated into a severance payment or a firing tax. Instead, the law prescribes that the worker cannot be laid off unless some narrowly specified conditions are fulfilled. Most of the times, it is the task of the courts to find out whether these conditions are fulfilled. If the court finds out that a layoff was not valid a severance payment is usually fixed. This procedure entails a lot of uncertainty for the parties involved. Often times a worker refrains from a lawsuit if the firm pays him a severance payment directly. Thus, employment protection in Germany has evolved into a bargain on severance payments. These procedures can be interpreted as having elements of both a firing tax and severance payments. The analysis has shown that a severance payment has no positive effect on employment nor on training on the job. However, a firing tax does have positive effects as long as it is only moderate. The analysis has shown that the reduction of employment protection can indeed help enhance employment for young workers. For workers above the age of 47, it will rather have a disadvantageous effect. Therefore, politics should first identify the target group of a policy and then take suitable provisions. If the aim is to increase employment of older workers, the relaxation of EP appears not to be the appropriate measure. Human capital formation is not the primary target of such policies, however it is an important policy issue. If EP were to be abolished, the reform should be accompanied by compensating measures, like subsidies for training. The next chapter attempts to carry the theoretical hypothesis of this chapter to the data.

One result of this chapter is that a firing tax can be an effective policy tool but a mandated severance payment is not. Under the wage setting regime assumed in this model, a severance payment reduces profits and therefore vacancy creation. It does not increase the firms' incentives to invest in the workers' human capital. Therefore, a firing tax should be preferred over a mandated severance payment.

This study is restricted to the effect on the firm's incentives to invest in the training. The worker's incentives have not been considered. The motivation for this approach derives from the fact that most training is initiated by firms and financed by them (see Chapter 3). However, the worker's motivation for training deserves also attention: Will employment protection make him invest more in relationship-specific capital? Or will the worker, as he is secure from layoff, put less effort in working? It would be also interesting to simulate the model under the assumption that the firms can observe only the worker's age before hiring, but not his level of human capital.

This study contributes further to the literature of human capital and income distribution. It shows how human capital formation and the labor market interacts and can thus be useful in explaining diverging distributions of income.

Appendix 2.A
Proof that $\min\{J^N, J^{min}\} > -\tau + S \Rightarrow w^N > w^{min}$

$$
\begin{array}{llll}
 & \min\{J^N, J^{min}\} & > & -(\tau + S) \\
\Rightarrow & J^N > -(\tau + S) & \wedge & J^{min} > -(\tau + S) \\
\Rightarrow & J^N = y - \mu(y - c + \beta\mathcal{E}^J + \tau + S) + (1-\mu)(\mathcal{E}^W - U - S) - c + \beta\mathcal{E}^J & > & -(\tau + S) \\
\Rightarrow & (1-\mu)(y - c + \beta(\mathcal{E}^W + \mathcal{E}^J)) & > & (1-\mu)(U - \tau) \\
\Rightarrow & \mu(y - c + \tau + \beta(\mathcal{E}^W + \mathcal{E}^J)) & > & \mu U \\
\Rightarrow & \mu(y - c + \beta + \tau + S) - (1-\mu)(\beta\mathcal{E}^W - U - S) & > & U + S - \beta\mathcal{E}^W \\
\Rightarrow & w^N & > & w^{min}
\end{array}
$$

q.e.d.

Appendix 2.B
Solving the model

This model is solved by dynamic programming in discrete time with a finite horizon. The state of a firm-worker match can be characterized by the state variables, h and t. Each period the firm chooses investment I_t and decides on whether the worker will be laid off or not. This decision can be characterized by the variable R_t, which corresponds to the reservation level of the skill shock. If the realization of the skill shock falls below this value the worker is laid of, if the shock realizes above, the match is retained. The wage, w_t, is determined by Nash-bargaining. The three variables I_t, R_t, and w_t are the control variables of the model. When choosing the values of these variables the agents take into account the consequences on future variables.

To solve the model, I begin in the last period of the worker's career, T. In this period there is no uncertainty about future shocks. The worker knows that he will retire after T. Therefore, the continuation value in this period is zero, and worker's present discounted utility is simply given by the wage he earns in that period:

$$W_T = w_T. \tag{2.35}$$

In the last period the worker does not take any training. The skill investment is zero,

$I_T = 0$. Therefore, the value of the job to the firm is given by

$$J_T = Zh_T^\alpha - w_T.$$

The firm's outside option is to lay off the worker. In this case it has to pay the firing tax and/or the severance payment, $\tau + S$. The worker's outside option is the value of being unemployed, b, plus the severance payment he receives in the moment he is laid off. Therefore, the Nash product in the last period is

$$(Zh_T^\alpha - w_T + (\tau + S))^{1-\mu}(w_T - (b + S))^\mu.$$

Maximizing the Nash product with respect to the wage yields

$$w_T^N = \mu(Zh^\alpha + \tau + S) + (1 - \mu)(b + S),$$

where the superscript N denotes the outcome of the Nash-bargain. If the firm wants to keep the worker the firm must provide to the worker at least the utility that he can get outside of the firm, i.e. the firm must ensure that

$$W_T = w_T \geq b + S = S + U_T =: w_T^{min}. \tag{2.36}$$

However, from Appendix 2.A we know that $J_T < \tau + S$ whenever $w_T^{min} > w_T^N$. Therefore, the wage paid is always w^N, otherwise the match is severed. Thus, the job value in the last period is given by

$$J_T = Zh_T^\alpha - w_T = (1 - \mu)(Zh_T^\alpha - b - S) - \mu(\tau + S). \tag{2.37}$$

The firm's decision to keep the worker or to lay him off in the last period is characterized by the value of R_{T-1} which is chosen in $T - 1$. If the shock δ_T realizes above R_{T-1} the worker will be kept, if the shock falls below R_{T-1} the worker will be laid off. At $\delta_T = R_{T-1}$ the firm is indifferent between laying off and keeping the worker, i.e.

$$ZR_{T-1}^\alpha(h_{T-1} + I_{T-1})^\alpha = b - \tau.$$

Solving for R_{T-1} yields

$$R_{T-1} = \left(\frac{b - \tau}{Z}\right)^{1/\alpha} \cdot \frac{1}{h_{T-1} + I_{T-1}}.$$

The probability that the shock falls below this value is given by $F_\delta(R_{T-1})$. R_{T-1} depends on the worker's human capital at the end of period $T-1$ which is given by $h_{T-1}+I_{T-1}$.

In period $T-1$ the firm also chooses I_{T-1}. Given the investment cost function $c(I,h)$, the firm maximizes

$$\begin{aligned} -c(h,I) &- \beta F_\delta(R_{T-1})(\tau+S) \\ &+ \beta \int_{R_{T-1}}^{1} (Z(h_{T-1}+I_{T-1})^\alpha x^\alpha - b - S) - \mu(\tau+S) dF_\delta(x). \end{aligned} \tag{2.38}$$

The result is a policy function $I_{T-1}(h_{T-1})$. A worker who is unemployed in $T-1$ does not receive any investment. Therefore, his human capital evolves according to $h_T = h_{T-1}\delta_T$. A firm has also the possibility to post a vacancy in period $T-1$ for a specific worker type. The worker type is characterized by the tuple $(h_{T-1}, T-1)$. If the firm finds a worker in $T-1$, a match is formed. This match can produce output in period T. However, before production starts a skill shock arrives. The reservation value of the skill shock for a worker who was unemployed in $T-1$ is given by:

$$R^u_{T-1} = \left(\frac{b-\tau}{Z}\right)^{1/\alpha} \cdot \frac{1}{h_{T-1}}.$$

The superscript u indicates that this reservation value refers to a worker who was unemployed in $T-1$. Therefore, the expected value of a match to the firm in $T-1$ is given by

$$\begin{aligned} J_{T-1} = &- \beta F_\delta(R^u_{T-1})(\tau+S) \\ &+ \beta \int_{R^u_{T-1}}^{1} (Z(h_{T-1})^\alpha x^\alpha - b - S) - \mu(\tau+S) dF_\delta(x). \end{aligned} \tag{2.39}$$

As all firms are profit maximizing, labor market tightness, θ, is determined by the following condition:

$$\kappa = q(\theta_{ht}) J_{T-1} \qquad \forall h, t. \tag{2.40}$$

Now, I have enough information to calculate a worker's outside option in period $T-1$ by using equation (2.9). Then, I can calculate optimal wage and investment in period $T-1$ and determine the shapes of the value functions. For each period I approximate the value functions on a grid of the state variables h_t and t. I use shape-preserving splines for these approximations. The approximated value functions are used in the next step to compute the optimal policy values in the period before.

I proceed in this manner until I have reached the first period. The solution are policy functions

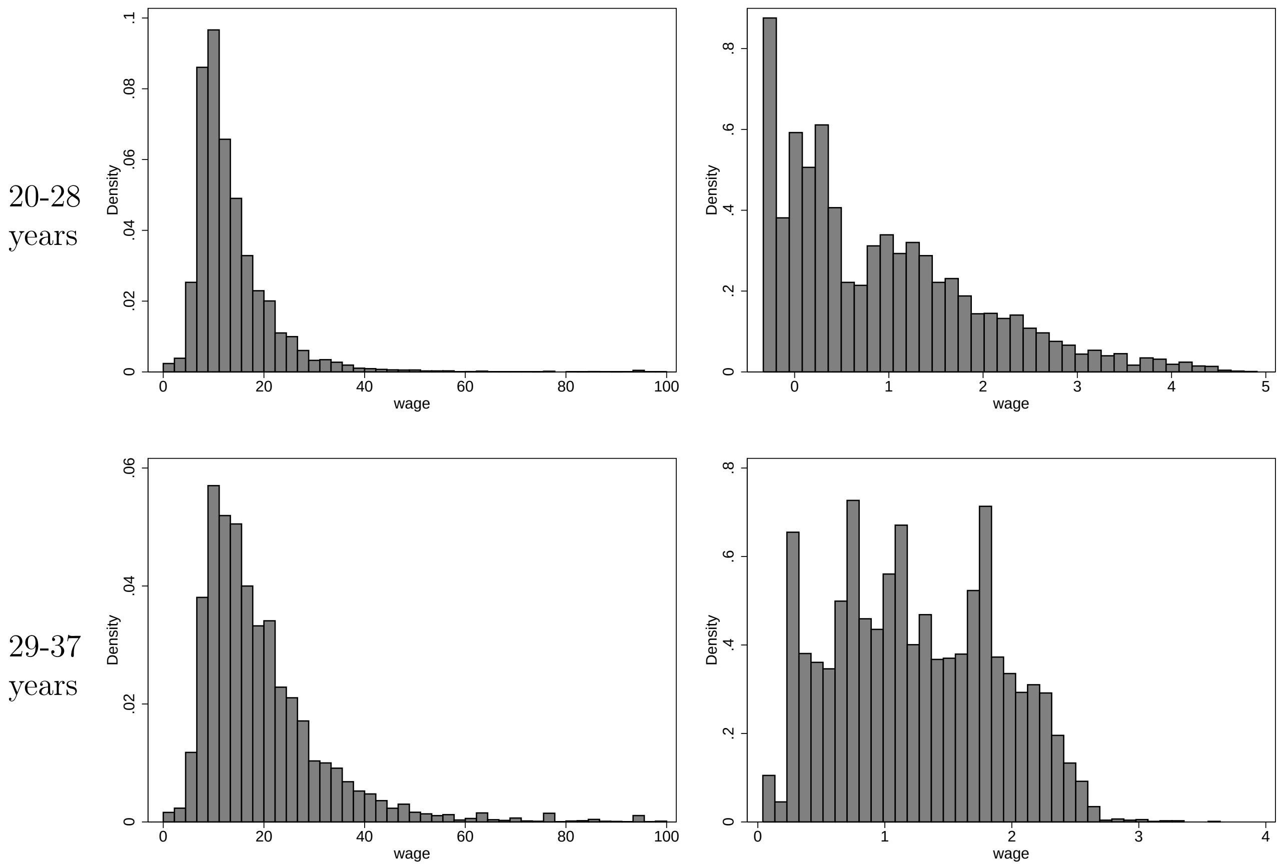
$$w(h,t), \quad I(h,t), \quad R(h,t) \qquad t = 1, ...T \tag{2.41}$$

that determine the wages, the investments and the layoff decisions in each period. Figures 2.11 to 2.12 in Appendix 2.C depict the policy functions for the wage and investment.

Appendix 2.C

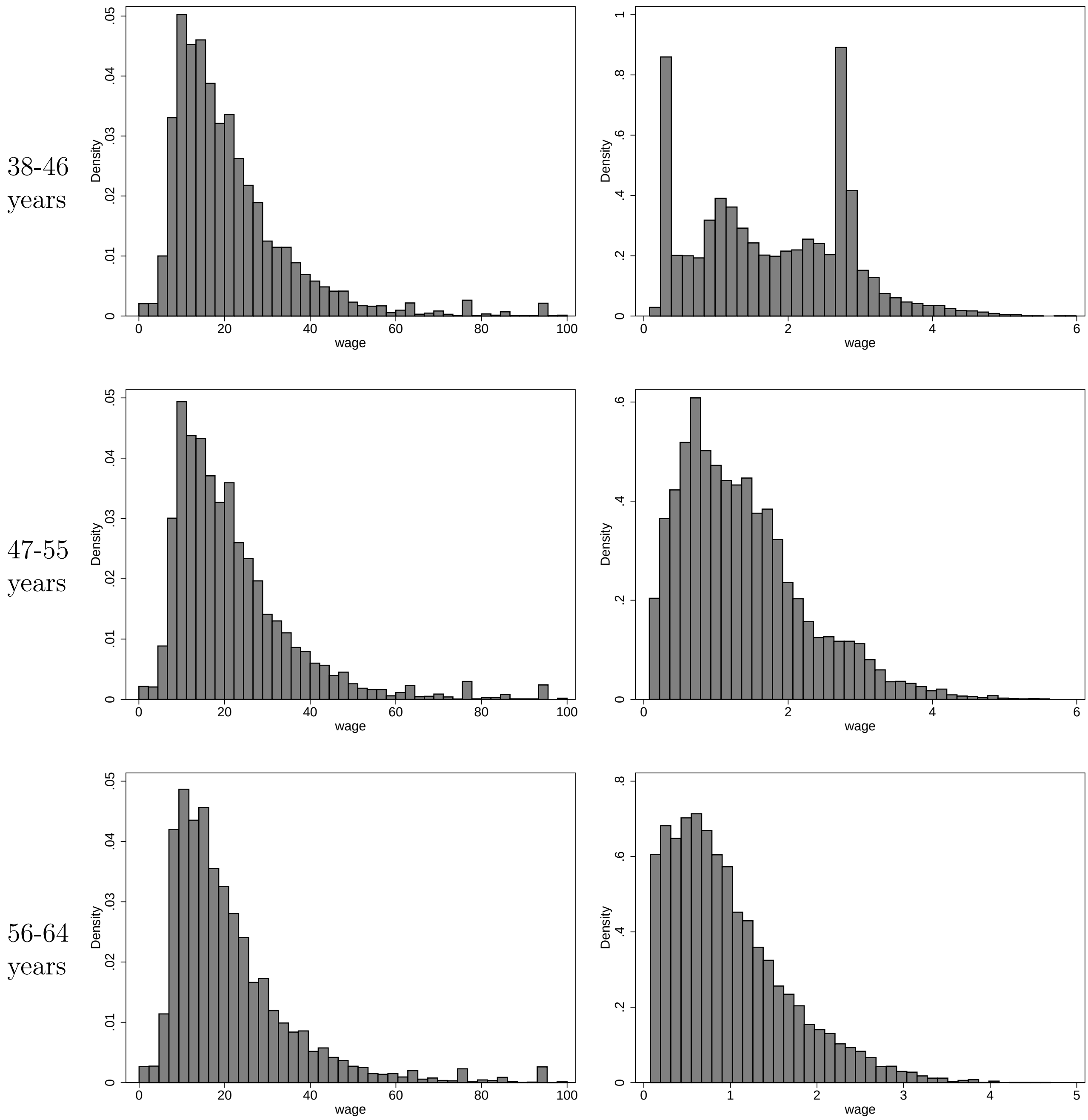
Additional figures

Figure 2.10: Evolution of the wage distribution



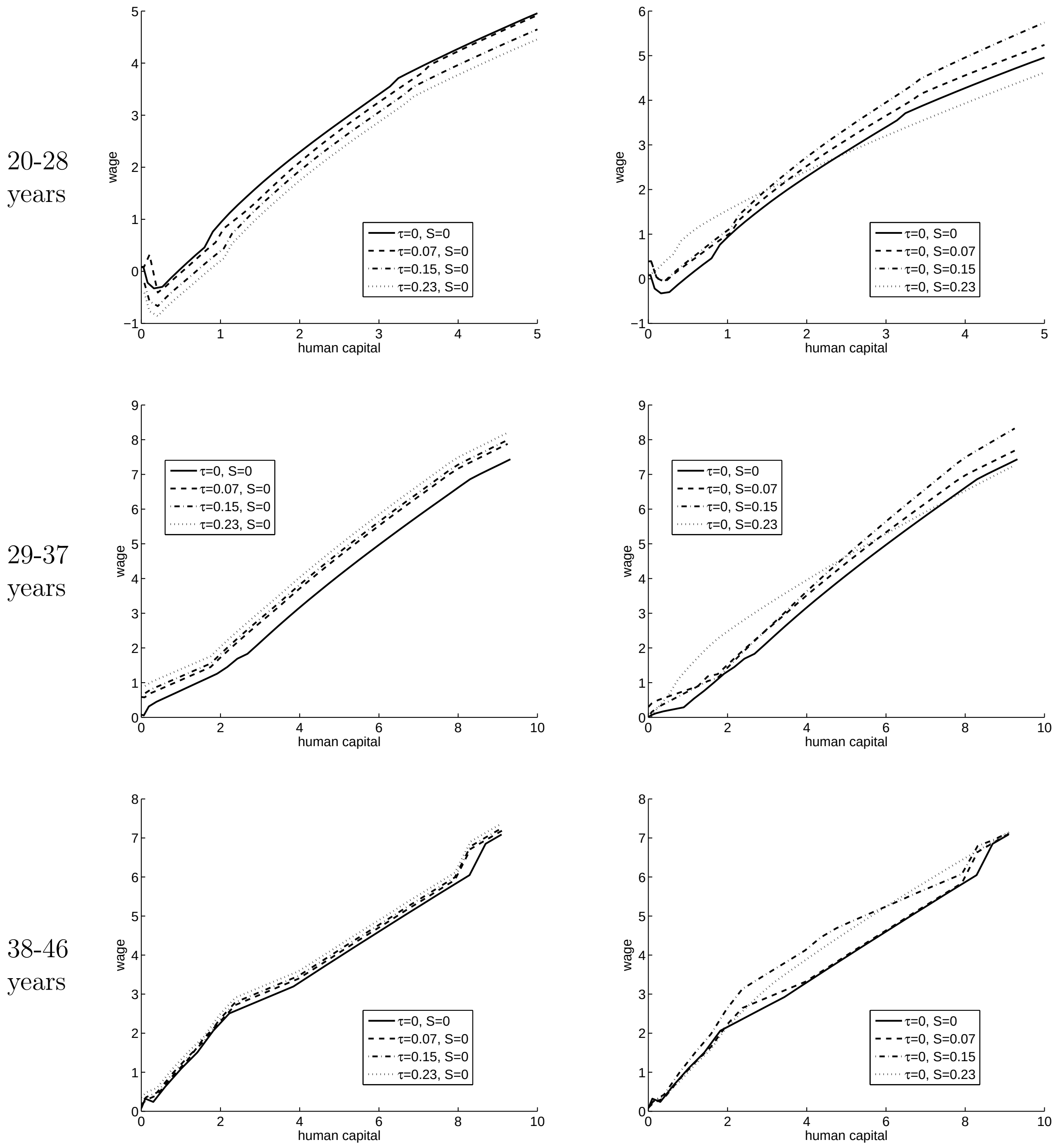
Evolution of the wage distribution in the CPS (left column) and in the model (right column).

Figure 2.10: Evolution of the wage distribution (cont'd)



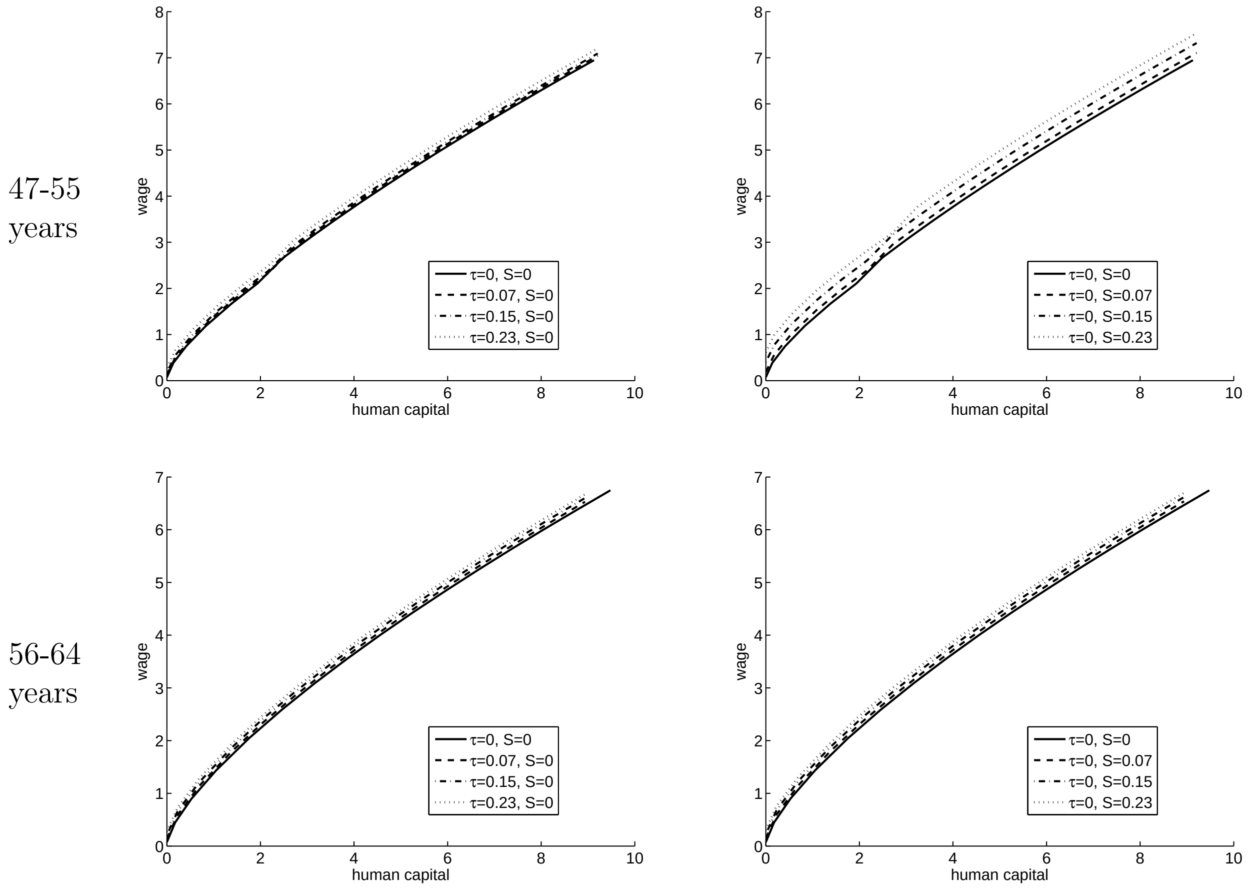
Evolution of the wage distribution in the CPS (left column) and in the model (right column).

Figure 2.11: Policy functions: wage setting



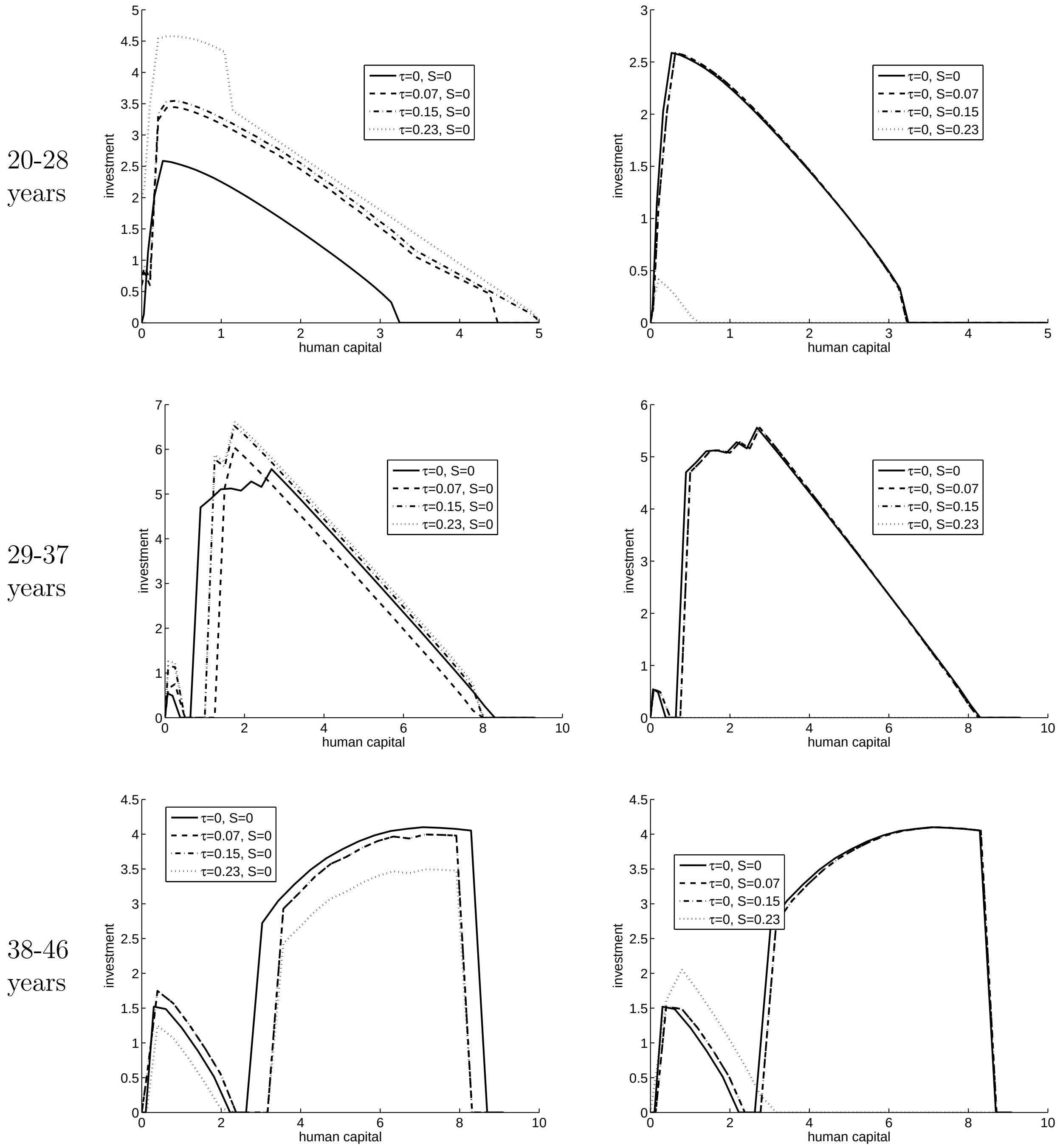
Wage function for different levels of a firing tax (left column) and severance payment (right column).

Figure 2.11: Policy functions: wage setting (cont'd)



Wage function for different levels of a firing tax (left column) and severance payment (right column).

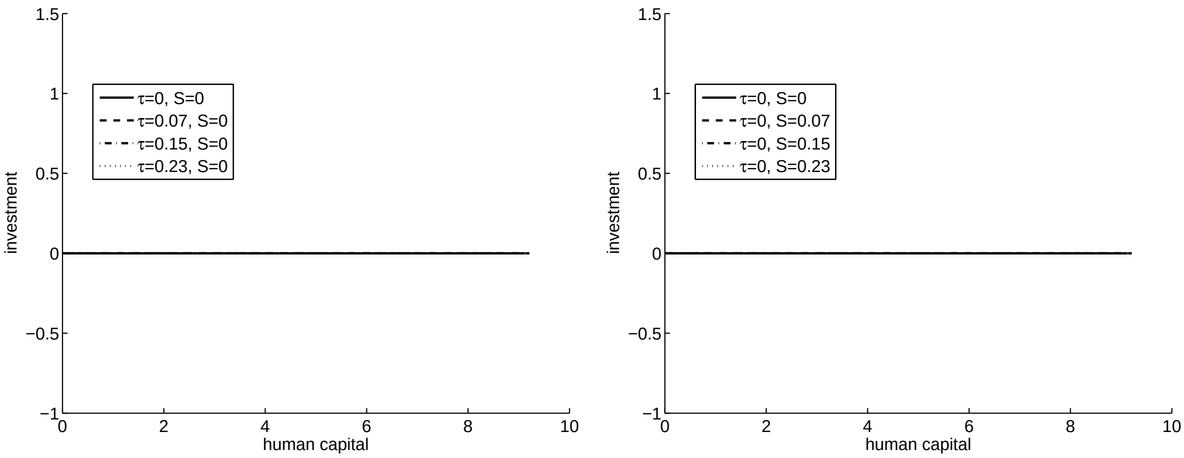
Figure 2.12: Policy functions: investment



Investment function for different levels of a firing tax (left column) and severance payment (right column).

Figure 2.12: Policy functions: investment (cont'd)

47-55 years



Investment function for different levels of a firing tax (left column) and severance payment (right column).

Chapter 3

Employment Protection and Training Incidence

In this chapter I examine the relationship between employment protection and on-the-job training empirically. Ideally, I would compare the impact of labor market institutions on training in several countries. There are indeed a few international surveys on training.[1] However, such an international comparison is difficult because training behavior is influenced by many factors other than labor market institutions. Assessing the impact of labor market institutions on training in a country would require to control for all the other factors that influence training behavior, especially policies of education. This would go beyond the scope of this study. Therefore, I restrict the analysis to one country - Germany. Germany is of special interest because employment protection legislation has been in the political debate for several years and has been changed several times during the last fifteen years. This enables me to consider the changes in legislation as a "natural experiment" and analyze their consequences.

In the first section of this chapter, I will give an overview of how professional training has evolved in Germany during the last fifteen years and document some facts. For this purpose I will use data from the survey "Berichtssystem Weiterbildung" (BSW)[2] which is run by the Federal Ministry of Education and Research. In the subsequent section, I will do some econometric analysis to evaluate a potential relationship between employment protection and the development of professional training. I will employ the technique of difference-in-differences to find out whether the change of legislation has had an influence on participation in professional training. In this analysis I will estimate a linear probability model and a probit model. I will use data from the survey "Qualification and Career Survey" wich is conducted by the Federal Institute of Professional Training (BIBB). Both

[1] One example is the new CVTS run by Eurostat.

[2] The English translation of the German name is "Report system professional training".

data sets have been used in analyses of the German labor market, for instance by Puhani and Sonderhof (2008). They also estimate a difference-in-differences model analysis and investigate the impact of changes in the laws of maternal leave on training participation of young women. An overview over different German surveys that contain information about training on- and off-the job is given by Seidel (2006).

3.1 Professional training in Germany

Table 3.1: BSW: structure of the data set

Number of observations	1988	1991	1994	1997	2000	2003	Total
Gender							
male	1,717	955	1,281	1,271	1,315	1,419	7,958
female	1,055	735	722	845	927	1,088	5,371
Age							
19-28	767	419	424	386	390	422	2,807
29-37	567	404	594	626	631	640	3,461
38-46	580	382	444	551	614	705	3,276
47-55	604	356	357	354	400	487	2,558
56-64	253	128	185	200	208	253	1,227
Total	2,771	1,689	2,003	2,117	2,242	2,507	13,329

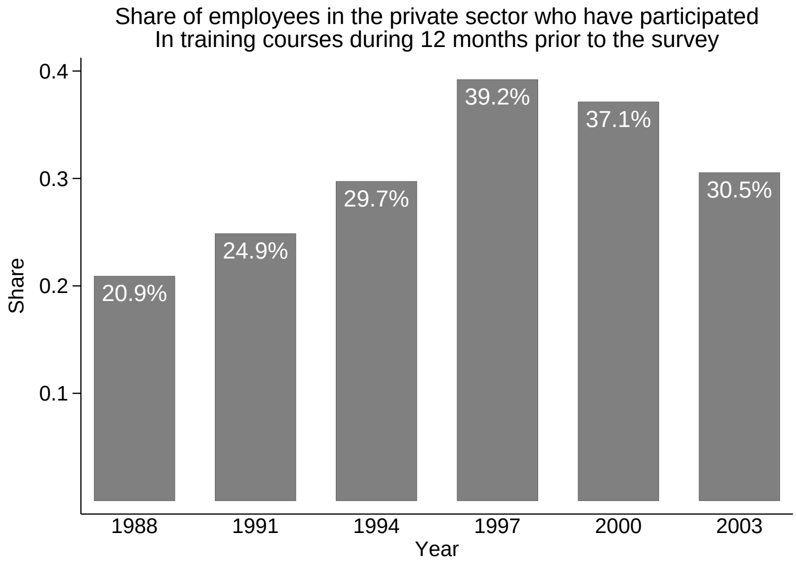
(Columns 1988–2003 under the header **Year**.)

Berichtssystem Weiterbildung (BSW), structure of the data set: number of observations in each cell. Numbers are adjusted by sampling weights. Only observations of employed individuals in the private sector in West Germany are counted.

The *Berichtssystem Weiterbildung* (BSW) is a survey commissioned by the federal ministry of education and research (BMBF). It was started in 1979 and has been followed every three years ever since. Data for the years 1982 and 1986 are not available. Therefore, I start the analysis in 1988 and go until 2003, the latest sequel available. The population of the survey are all individuals who are older than 19 years and younger than 65 years, living in private households in Germany. Approximately 7000 people are interviewed each time. The survey asks employed and non-employed people about participation in training activities. Here, I only consider employed people. The survey is designed in such a way that it is representative for the German workforce.

I limit the analysis to German citizens living in West Germany, in order to avoid two types of discontinuities: 1. Due to the reunification in 1990 the survey was extended to the Eastern part of Germany, for the first time in 1991. 2. Before 1997, only individuals

Figure 3.1:
Participation in training measures

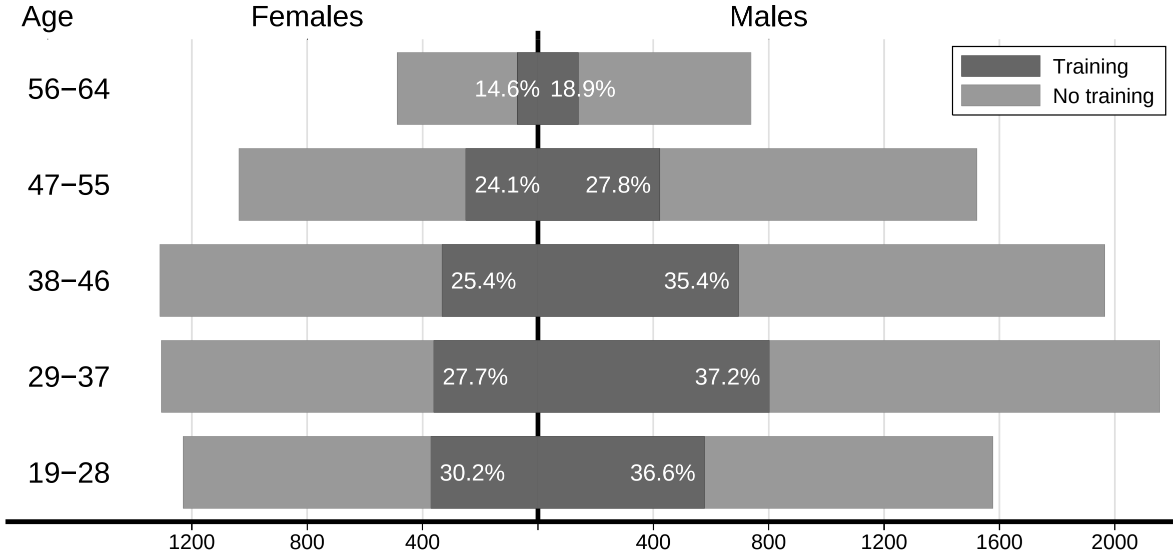


Source: Berichtssystem Weiterbildung (BSW)
Notes: This figure shows the percentage of employees who report to have participated in a training course during the 12 months prior to the survey. The population are all employees in the private sector having the German citizenship and living in West Germany. Only people who are employed at the time of the survey are included. Self-employed are excluded. The twelve month period corresponds to the corresponding calendar year. In 1988, 1991, 1994 the twelve months refer to the period from October of the preceding year until September of the corresponding year. The survey is representative for the German workforce.

holding the German citizenship were interviewed, from 1997 onwards, the interviews were extended to the foreign population living in Germany. I also exclude the public sector because in the public sector the incentives to provide training are of different nature than in the private sector and in the public sector many employees enjoy a special type of employment protection.[3] I also exclude self-employed. Table 3.1 reports the number of observation in each year per gender and per age-cell. The age-cells are chosen to match those used in the theoretical assessment in Chapter 2. The survey includes more males than females because participation is lower for the latter. From 1991 the sample of West Germany is smaller due to the inclusion of East Germany in the survey. The survey asks people about their participation in training, both of the type professional and general training. I am interested in the professional training type. The interviewees are

[3]Employees who have been working for 15 years for the same employer in the public sector and who are older than 40 years cannot be laid of at all. However, this applies only to West Germany.

Figure 3.2: Composition by age and gender



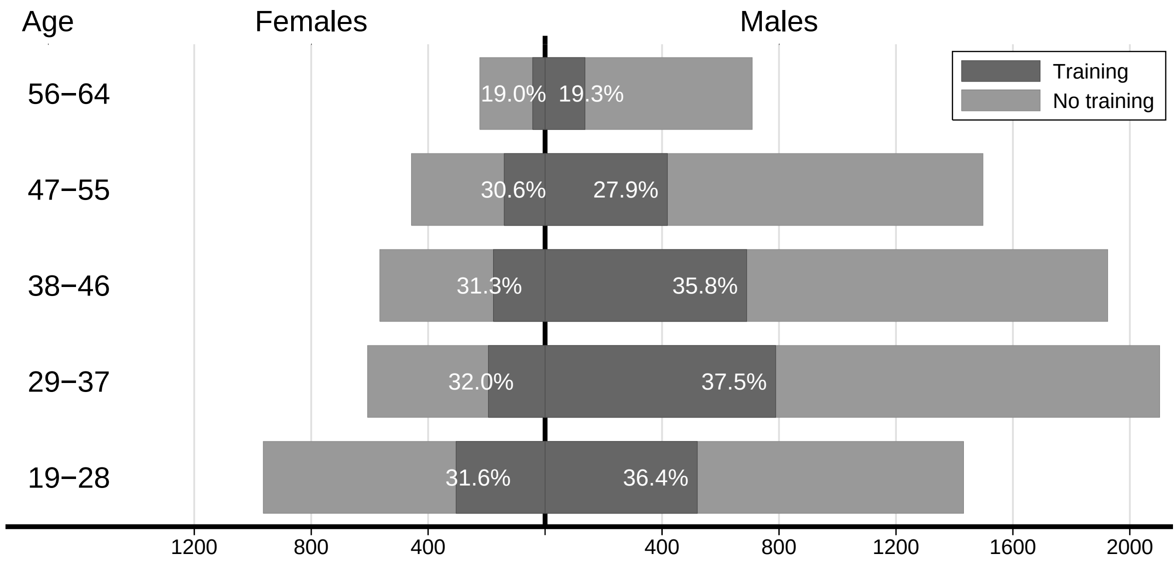
Source: Berichtssystem Weiterbildung (BSW)
Notes: Composition of the data set by age and gender. The length of the bars corresponds to the number of observations in the corresponding cell. Percentages report the share of individuals who have participated in training during twelve months prior to the survey. The population are all employees in the private sector having the German citizenship and living in West Germany. Only people who are employed at the time of the survey are included. Self-employed are excluded.

given a list of training measures and are asked whether they have participated in one or several of these measures. The list gives the following points: Courses that help to change occupation, courses that prepare an ascension to a higher position or occupation, courses that prepare for a new type of tasks and "other courses in my profession". Figures 3.1 to 3.4 give information about the *reach* of professional training. Figure 3.1 shows the percentage of workers who have participated in professional training. Participation rose during the 1990s, marked a peak in 1997 and has declined since then.[4]

Figures 3.2 to 3.4 further characterize the workers who actually receive training. Figure 3.2 depicts the composition of the dataset by age and gender. It shows that male workers participate more in training. The reason for this is that women hold part time jobs more frequently than men. Part time workers participate less in professional training than full time workers do (29% vs. 36% in 2003). In 2003, 70% of male workers were full time, but only 29% of female workers. If only full time workers are considered, the difference in participation rate diminishes as can be seen from Figure 3.3. In the last year of the

[4]Part of the decline in training can be explained by the reduction of publicly funded training triggered by the readjusted of public funding for professional training in the course of the so-called "Hartz-I"-reform which came into force at the beginning of 2003 (IZA, 2006). However, this segment is so small that it can explain only a fraction of the decline observed in the data.

Figure 3.3: Age and gender, only full-time workers

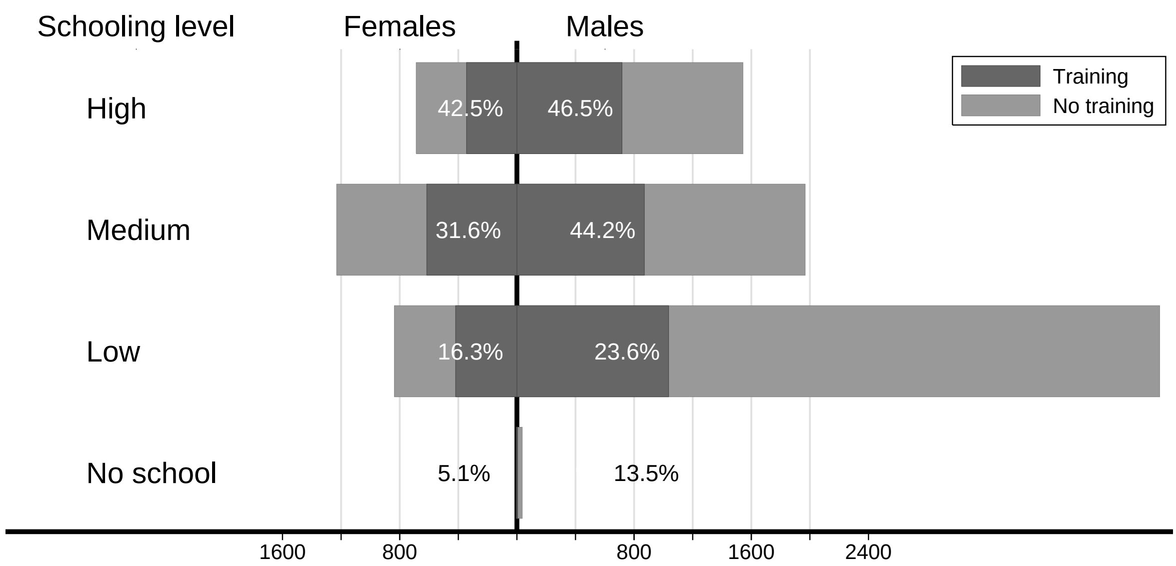


Source: Berichtssystem Weiterbildung (BSW)
Notes: Composition of the data set by age and gender. Only fulltime workers. The length of the bars corresponds to the number of observations in the corresponding cell. Percentages report the share of individuals who have participated in training during twelve months prior to the survey. The population are all employees in the private sector having the German citizenship and living in West Germany. Only people who are employed at the time of the survey are included. Self-employed are excluded.

survey, 2003, the women's rate, 40%, even exceeds the men's rate, 34% (Kuwan, Bilger, Gnahs and Seidel, 2006, p. 122). The figures show that old workers participate less in training than middle-aged workers. Most training is given to workers at the ages between 29 and 46. Figure 3.4 decomposes the data set into groups by gender and schooling level. To the one who has, more will be given: the higher the worker's schooling level the more likely (s)he is to participate in professional training during the working career. Those who left school without a degree participate the least in professional training - 23.3% of male workers in this group have participated in professional training and only 5.1% of female workers. The figure also reveals that in the data set the group of workers with a low level of schooling is the largest.

The focus of the theoretical assessment in chapter 2 has lain on training that is organized and funded by firms. The following graphs give information about the share of training funded by firms and provide some justification for that approach. Figure 3.5 depicts the average number of courses per employee. Contrary to Figure 3.1 this figure does not count *individuals* who participated, but *cases*, i.e. the number of training measures that were done. People are asked in how many courses they have participated. The total number of all courses are divided by the number of employees in order to be able

Figure 3.4: Composition by gender and education



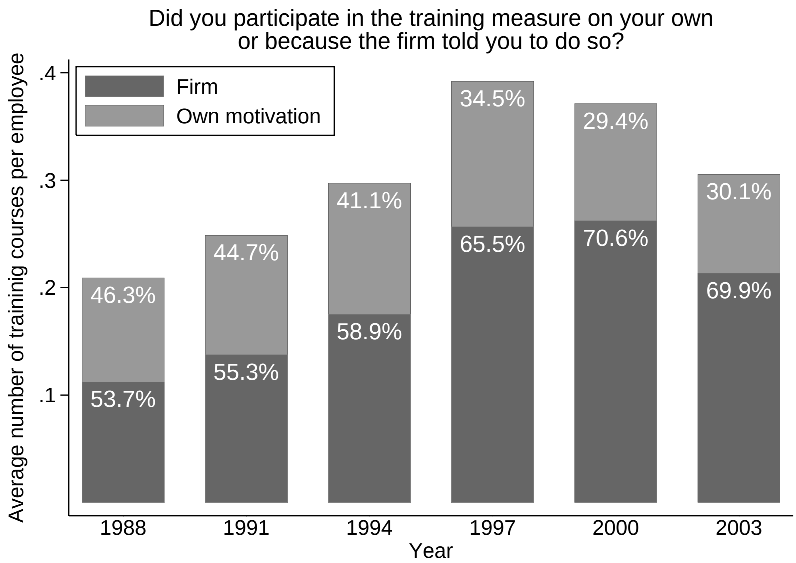
Source: Berichtssystem Weiterbildung (BSW)
Notes: Composition of the data set by education and gender. The schooling level referres to the highest schooling certificate obtained (low: Hauptschule, medium: Mittlere Reife, high: (Fach-)Abitur) Percentages report the share of individuals who have participated in training during twelve months prior to the survey.

to compare the number of courses across surveys.[5] Again, I only consider individuals in the private sector living in West Germany. Self-employed are excluded. The graph confirms the insight from Figure 3.1 that training peaked in 1997. The percentage numbers give information about the motivation to participate in training. For each course, the workers were asked why they participated in it. They show the ratio of courses that were attended because of three different types of motivation: 1: The firm required the individual to participate, 2: A superior recommended the course, 3: The worker attended the course because of private interest. I labeled motivation 1 and 2 as "firm". It shows that the greatest part of training measures are mandated by the employer. The 100% comprises all valid answers of 1, 2, and 3. Courses where the individual did not answer the motivation question are counted in the absolute number of courses, but are not counted in the 100% of the motivation-question.

In the BSW the individuals are asked whether they have received financial support from their employer for the course. Figure 3.6 shows the percentage of courses for which the individual received at least some support from his employer. In line with the findings by Loewenstein and Spletzer (1999) most of the training is sponsored by firms. Unfortu-

[5]In 1988, one employee can report up to seven training courses. Therefore, also in the subsequent years I do not count more than seven courses per individual.

Figure 3.5: Motivation for professional training

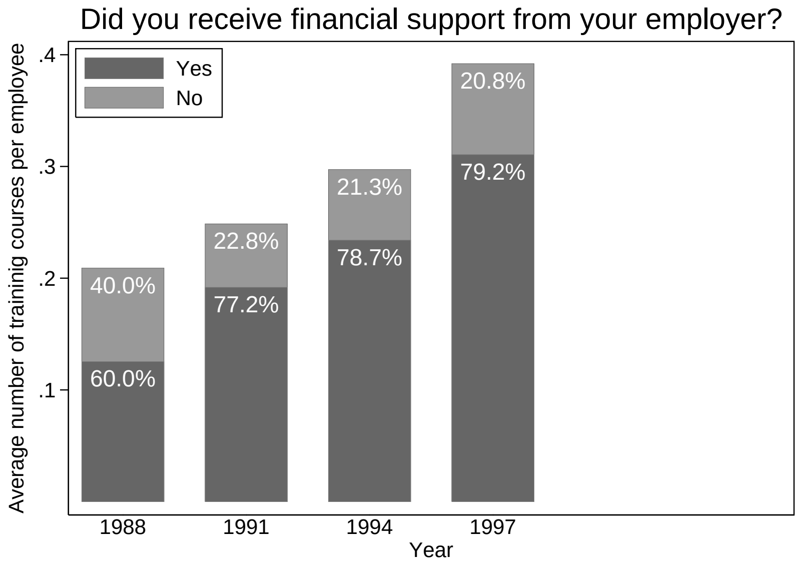


Source: Berichtssystem Weiterbildung (BSW)
Notes: Number of courses per employee: absolute number of courses during the last 12 months divided by the number of employees in the sample. The percentages refer to the motivation of participation. People answered that they participated on their a) own motivation, b) because the firm requires it or a superior recommended participation in the course to them.

nately, this question was not included in the surveys of 2000 and 2003. Additional light on this aspect is shed by the question whether the individual had to cover any cost of the course. The results of this question are reported in Figure 3.7. As the graph shows, for the greatest part of the courses the individual did not have to pay. Figure 3.8 gives some information about possible production losses related to training. More than two thirds of the training measures take place during working time. About ten percent of measures take place at least partly during working time. This gives some evidence that training is indeed related to loss of production for the employer.

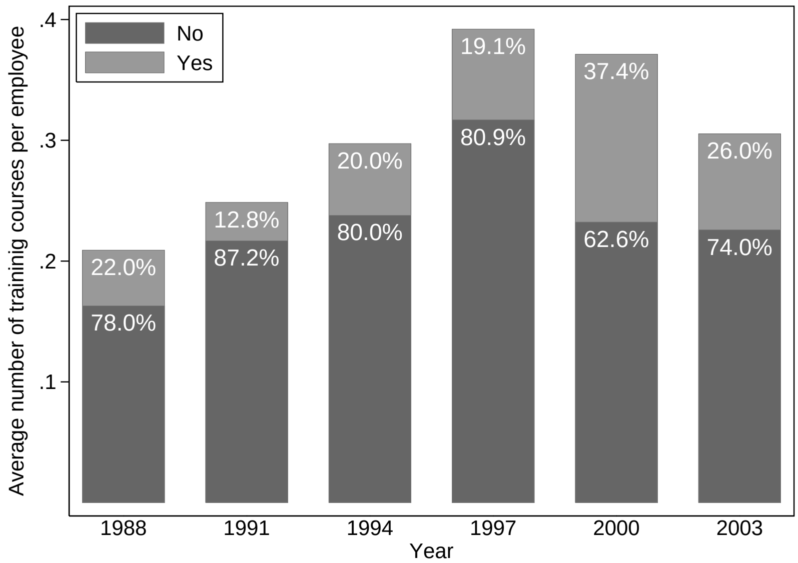
In summary, the findings of the BSW indicate that a great (about half) of professional training is mandated by firms, and firms cover a large part of the direct cost of the training measures and that most training measures are also linked to production losses. These findings are in line with the results obtained by Loewenstein and Spletzer (1999) and by Barron et al. (1999), for the United States.

Figure 3.6: Financial support from employer



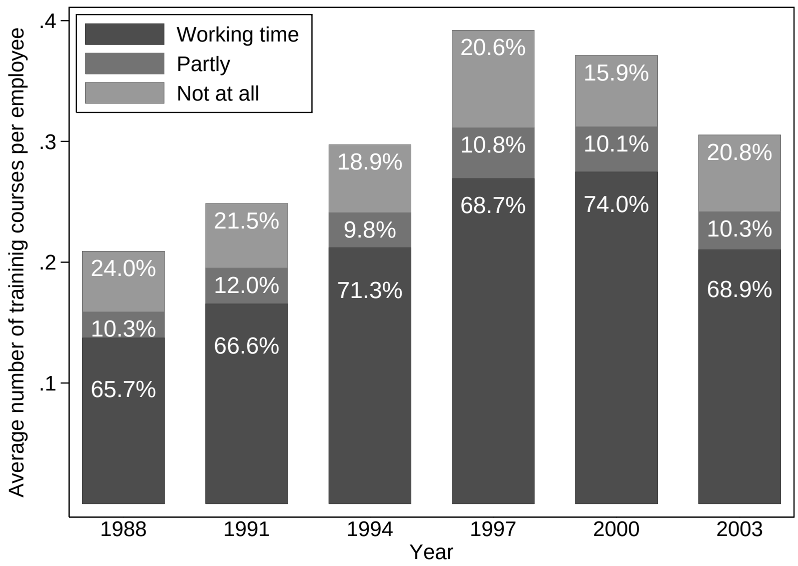
Source: Berichtssystem Weiterbildung (BSW)
Notes: The percentages refer to the number of courses where the individual received at least partial support from their employer - and where the individual not not receive any support from the employer, respectively. This question was not included in the surveys of 2000 and 2003.

Figure 3.7: Did you have to pay for the training measure?



Source: Berichtssystem Weiterbildung (BSW)
Notes: The percentages refer to the number of courses where the individual had to pay some participation fee.

Figure 3.8: Did the course take place during working time?



Source: Berichtssystem Weiterbildung (BSW)
Notes: The percentages refer number of courses that have taken place during working time, not during working time or partly during working time.

3.2 Regression analysis difference-in-differences

In this section I approach the relationship between employment protection and training empirically. The legislation of employment protection has been changed several times in the 1990s. Two of these reforms are of special interest because they changed the scope of the law. I can use these reforms as a natural experiment. Before 1996, establishments with *five or fewer employees were exempted* from employment protection. On October 1st, 1996, this threshold was raised, from then on, establishments *with ten or fewer* employees were exempted from employment protection. However, this regulation was in force only three years: on January 1st, 1999, the regulation went back to the old regime. I will check if the change in 1996 had an influence on the behavior of firms to train their employees. In order to do this I need to identify those firms that were affected by the change in the employment protection act, namely those that have six to ten employees. Unfortunately, the BSW contains information about establishment size only in size-classes which do not correspond to the size classes of the employment protection act. The BSW uses size classes of 1-4, 5-19, 20-99, 100-499, 500-999, 1000-1999, 2000 and more employees. The establishments that underwent a legislative change are all included in the size class of 5-19 employees, but there are too many other firms included in the same size class that did not undergo a legislative change. Therefore, in order to do the regression analysis I use a different survey that contains more detailed information about establishment size: the survey *Qualification and Career*.

I will estimate a probit model and a linear probability model. For identification I employ a difference-in-differences technique. I am not the first to explore the effects of the legislative change of the employment protection act by the difference in difference technique. Bauer et al. (2007) use this methodology to analyze the effects of the changes in the law which were introduced in 1996 and in 1999 on the propensity of firms to employ workers. They did not find a significant influence of the change of employment protection on the worker flows.

3.2.1 Data from the Qualification-and-Career Survey

The survey *Qualification and Career* (QuB) is run by the federal institute of professional training (Bundesinstitut für Berufliche Bildung - BIBB). This survey interviews employed people all over Germany and asks questions about their professional development and their education. It is available for the years 1979, 1985, 1992 and 1999 contains about 15,000 observations each time. Therefore, it is larger than the BSW. Additionally, it covers a broader scope of topics, however in less detail. The QuB has not got as detailed questions about each individual training measure, it merely asks “Now, think about the last five

Table 3.2: Establishment size classes

Establishment size class (employees)	No. of observed employees 1992	1999	Total
1- 4	1,499	2,105	3,604
5- 9	2,641	3,001	5,642
10- 49	5,348	5,930	11,278
50- 99	2,510	2,186	4,696
100-499	4,325	3,541	7,866
500-999	1,394	1,038	2,432
1000 and more	3,357	2,150	5,507
sum	21,074	19,951	41,025

Source: Qualification-and-Career survey

years. During this period, have you attended courses, trainings or seminars serving as further education in your profession or as a reeducation for another profession?" This question about training covers a larger time period than the BSW (five years as opposed to one year). The wording of the question is not as detailed as in the BSW.[6] Therefore, test persons are more likely to make mistakes answering. However, there is a piece of information in the QuB which is reported in more detail than in the BSW and which is of particular importance to my exercise. That is the information about establishment size. As in the BSW, this information is given in the form of size classes. The size classes in the QuB (1992) are: 1-4, 5-9, 10-49, 50-99, 100-499, 500-999, 1000 and more.[7] I will use the establishments of 5-9 employees as the treatment group as it comes closest to the group actually affected by the change in legislation in 1996 (6-10 employees). Still, these size classes are not identical to the size classes as defined by the employment protection act, but they coincide to a large part. There are further differences: the definition of employees counted in the data set is different from the definition of the employment protection act. In the data set, the owner of the firm and apprentices are counted as employed people, whereas in the employment protection act both groups are not counted. Further differences arise in the way in which part-time employees are counted. The law has some very sophisticated regulations how these are counted, in the survey the respondents are simply asked "How many people are employed in your establishment" without referring to whether people are part time or full-time employed. Therefore, in the survey establishment

[6] Compare the wording of this question to the wording of the BSW given in Section 3.1. Whereas the BSW gives a detailed list of purposes what the trainings could be aimed at, the QuB uses a more general formulation.

[7] In 1999, the QuB divides the class of very small establishments into even smaller classes of 1, 2, and 3-4 employees.

size tends to be over-estimated with respect to the law. The establishments which are affected by the respective changes of the law in 1996 and 1999 will be found in the size classes of 5-9 and 10-49. An additional difficulty arises because the law was applicable only to new hires after 1996. If an individual worked in an establishment that had between 6 and 10 employees in 1995, (s)he was still protected from dismissal, even after the reform. Nevertheless, I will use the size class of 5-9 as the one which is affected by the changes in the employment protection act and all other size classes as “not affected” hoping that the share of affected establishments in this size class is high enough to find an effect. In the benchmark estimation I will consider all workers of those firms as the treatment group. As a robustness check I will estimate the model and count as the treatment group only those workers who have a tenure of less than tree years.

Table 3.3: Training participation by establishment size

Establishment Size	Participants		Non-participants	Total
1- 4	2,645	(73%)	959	3,604
5- 9	4,101	(73%)	1,541	5,642
10- 49	7,824	(69%)	3,454	11,278
50- 99	3,283	(70%)	1,413	4,696
100-499	5,043	(64%)	2,823	7,866
500-999	1,446	(59%)	986	2,432
1000 and more	2,989	(54%)	2,518	5,507
sum	27,331	(67%)	13694	41,025

Source: Qualification and Career Survey
Notes: Number of observations in each category. Participation in training during the last five years and establishment size classes. The percentage number refers to the share of individuals that participate in training in the corresponding size class.

I use the QuB data from 1992 and 1999. The interviews of the 1992 survey were conducted in the period from November 1991 until end of February 1992. The 1999 survey was conducted from October 1998 until March 1999. From the 34,277 observations in 1992 and the 34,343 observations in 1999 I exclude all individuals who are under 20 years of age, those who are self-employed and those who work in the public sector. In 1992, the dataset contains an extra sample of unemployed people in East Germany that I also exclude. Additionally, I exclude observations if any of the control variables which I use in the regression is missing. At the end I am left with 41,025 observations, 21,074 in 1992 and 19,951 in 1999. As in this data set I don't have the problem with the German reunification, I can consider both West and East Germany. After categorizing the observations into establishment-size classes and according to participation in training measures it turns out that most individuals in the sample work in establishments of 10-

49 employees (Table 3.2). About 14% of the observations fall into firms of the size 5-9 employees which is the group of interest in the analysis. The size classes are of about the same size in both years. Table 3.3 decomposes the data set according to firm size and year of observation. It shows that the larger the firm the more likely is participation in training. Table 3.4 gives a decomposition according to age of workers and year of observation. It appears that training efforts have increased between both years of observation. Comparing Table 3.4 with the percentage numbers given in Figure 3.2 reveals that training incidence changes only a little when the period of observation is extended from one year to five years.

Table 3.4: Training participation by age

Age	1992		1999		Both Years	
	No obs.	of these participated in training	No obs.	of these participated in training	No obs.	of these participated in training
20 - 28	3,939	28.7%	3,229	28.6%	7,168	28.6%
29 - 37	5,804	36.4%	6,195	39.6%	11,999	38.1%
38 - 46	4,701	35.4%	5,278	39.4%	9,979	37.5%
47 - 55	4,494	27.2%	3,433	36.3%	7,927	31.1%
56 - 64	2,136	17.0%	1,816	27.5%	3,952	21.9%
Total	21,074	30.8%	19,951	36.1%	41,025	33.40%

Source: Qualification and Career survey
Notes: Number of individuals who report that they have participated in training courses during the last 5 years.

3.2.2 Econometric methodology

The simplest model that can be used to do this analysis is the *linear probability model* (Wooldridge, 2002). The variable to be explained is either participation or non-participation in training. This variable, denoted by $y(i)$, is one if the individual reports to have participated in training during the last five years, otherwise the value is zero. The model is of the following form:

$$y(i) = \alpha_1 d_t(i) + \alpha_2 d_s(i) + \alpha_3 d_t(i) d_s(i) + \beta x(i) + \varepsilon(i), \qquad y(i) \in \{0, 1\}. \tag{3.1}$$

In this equation, $d_t(i)$ denotes a dummy for observations in the year 1999, i.e. after the legislation was changed. $d_s(i)$ is a dummy for the observations in size class 5-9. The variable of interest is the interaction term of both dummies $d_t(i)d_s(i)$. The coefficient in this interaction term can be interpreted as the increase in the probability that an individual has participated in training due to the legislative change. The vector $x(i)$ includes a set of control variables such as (time-indifferent) dummies for the other establishment size classes, a dummy for gender, age, age squared, and dummies for education, position in job, industry, nationality (German or non-German), and one for East-Germany. The coefficients to be estimated are denoted by $\alpha_1, \alpha_2, \alpha_3$ and β.

The gender-dummy takes the value of 1 for females, 0 for males. Age is measured as the individual's age minus 23. There is a schooling dummy for each level of schooling: lower education (Hauptschule), intermediate level (Mittlere Reife), higher level (Abitur), one for those people who left school without certificate, and "other" for those people whose schooling certificate does not fit into one of these four categories. There is an additional dummy for those who have finished university or similar studies. Position in job is a dummy which takes the value of one if the person is blue collar (German: Arbeiter) and 0 if (s)he is white-collar (German: Angestellter). There are dummies for 39 industries and finally a dummy which takes the value of unity if the worker has German citizenship. I estimate this model by OLS. Whereas the dependent variable takes the value of either 1 or zero, the predicted value can take any value. If $\hat{y}$ denotes the predicted values, the error is either $1 - \hat{y}$ or $1 - \hat{y}$. Thus, there is heteroscedasticity by construction. To cope with this, I estimate the standard errors of the regression using the White-heteroscedasticity-robust estimator. The predicted values of the estimation correspond to the probability that one particular individual has participated in training. If this probability is above 0.5 the individual is predicted to participate, if it is below this value, the individual is predicted to not participate in training.

The coefficient on the treatment dummy can be interpreted as the increase in probability to participate due to the legislative change. I also estimate a probit model with the same parameters.

3.2.3 Regression results

Estimating a linear probability model I find a significant effect that the probability of participation in training has decreased by 3% due to the liberalization of employment protection legislation (Table 3.5). The coefficient on the interaction dummy is the average increase in probability that is due to the legislative effect, it is significant on the 5% level. This is remarkable because in the group of 5-9 establishments are also establishments included that were not affected by the legislative change. Therefore, the effect tends to be underestimated. The coefficients on the time dummies indicate that, in general, the probability for an individual has increased by 2.8% between 1992 and 1999. This is in line with the interpretation of Figure 3.1 from the last section. The coefficient on

Table 3.5: Estimation Results Linear Probability Model

	Coeff.	t-stat	Coeff.	t-stat
Group	-0.039 **	-5.50	-0.022 *	-2.39
1999	0.024 **	5.27	0.028 **	5.79
Interacted			-0.031 **	-2.58
Female	-0.093 **	-17.85	-0.093 **	-17.83
Age	0.011 **	16.89	0.011 **	16.89
Age squared	0.000 **	-19.62	0.000 **	-19.62
Schooling				
- no degree	0.060 **	4.38	0.059 **	4.35
- low degree	0.157 **	10.87	0.157 **	10.85
- intermediate	0.245 **	13.84	0.244 **	13.80
- high1	0.208 **	12.46	0.208 **	12.45
- high2	0.119 **	5.13	0.118 **	5.10
university	0.030 **	2.70	0.030 **	2.71
blue collar	-0.206 **	-37.66	-0.206 **	-37.68
foreigner	-0.105 **	-10.57	-0.104 **	-10.55
East Germany	0.047 **	7.91	0.048 **	7.97
No. obs	41,025		41,025	
F-Stat	F(58,41) = 151.73		F(59, 41) = 149.26	
PCP	71.34%		71.34%	
R^2	0.153		0.153	

Notes: Results from estimation of a linear probability model. Group is dummy for establishments of size 5-9 employees. "1999" is a dummy for observations in that year. The interaction is between these two dummies. Standard errors are calculated using the White-heteroscedasticity robust estimator. Controls included are: size classes (1-4, 50-99, 100-499, 500-999, 1000 or more), Age, Age squared, Dummy for female, 39 Industry-dummies, Dummies for different level of schooling: left school without degree, low degree (Hauptschule), intermediate degree (Mittlere Reife), High1 (Fachhochschulreife), High2 (Abitur), Dummy for graduates of university, dummy for blue-collar worker, Dummy for East Germany, Dummy for not-German citizens. PCP is the percentage of outcomes (participation or non-participation) that are correctly predicted by the model. Stars indicate significance on the 5%-level, double stars on the 1%-level.

the dummy for the group of establishments with 5-9 employees is -0.022 which indicates that the probability for a worker to take part in training is 2.2% less than the average. This is not surprising as we have already seen from the descriptive statistics that small establishments offer generally less training to their employees than bigger firms. The model predicts 71.34% of the outcomes (participation or non-participation in training) correctly. The regression results confirm the findings from the BSW: Female workers get less training. As we have found in the BSW, the level of schooling the worker enjoyed is also significant: Workers that have left school with an intermediate degree (Mittlere Reife or Fachhochschulreife) get the most training. Blue collar workers get less training than the white collar workers and people working in the Eastern part of Germany train more.

Table 3.6: Estimation Results Probit Model

	Ave. Marg. Effect	z-Stat	Ave. Marg. Effect	z-Stat
Group	-0.043 **	- 5.32	-0.027 **	-2.38
1999	0.028 **	5.68	0.032 **	6.07
Interaction			-0.030 *	-2.14
Female	-0.102 **	-17.93	-0.102 **	-17.92
Age	0.013 **	16.15	0.013 **	16.16
Age squared	0.000 **	-18.78	0.000 **	-18.79
Schooling				
- no degree	0.142 **	4.35	0.142 **	4.34
- low degree	0.256 **	7.52	0.256 **	7.51
- intermediate	0.352 **	9.44	0.352 **	9.43
- high1	0.313 **	8.55	0.313 **	8.54
- high2	0.232 **	5.48	0.232 **	5.47
university	0.022 *	2.05	0.022 *	2.05
blue collar	-0.220 **	-36.89	-0.220 **	-36.90
foreigner	-0.122 **	- 9.18	-0.122 **	- 9.17
East Germany	0.057 **	8.75	0.057 **	8.80
No. obs.	41,025		41,025	
LR-test	$\chi^2(58)$ =6672.58		$\chi^2(59)$ =6677.16	
PCP	71.39%		71.42%	
Pseudo R^2	0.128		0.128	

Notes: Results from Probit regression. Marginal effects reported are those that correspond to an average individual. Variables and controls are the same as in Table 3.5. Stars indicate significance on the 5%-level, double stars on the 1%-level.

The linear probability model has the advantage that it is simple in its methodology and delivers consistent results under fairly broad assumptions. On the other hand, the model is intrinsically misspecified because it delivers predicted probabilities outside of the unit interval. Also, it relies on equidistributed error terms, an assumption which is unlikely to be fulfilled and which cannot be verified. Therefore, I also estimate a probit-model with the same set of parameters. The results of this estimation are reported in Table 3.6. The marginal effects estimated by the probit model are similar to those estimated by the linear probability model. The probability change that is due to the change in legislation is estimated as -2.7% by the probit model which is similar to the effect estimated by the linear probability model (-3.2%).[8] As the linear probability model it predicts about 71% of

[8] I interpret the coefficient of the treatment variable as the treatment effect as suggested by Puhani

the observations (participation or non-participation) correctly. A problem for the Probit model is that it delivers consistent estimates only under more restrictive assumptions than the linear probability model. In the presence of heteroscedasticity the estimates are biased and inconsistent.

I estimate the same model also with a slightly modified definition of the treatment group: Now, I consider only those workers as part of the treatment group who have a tenure of less than three years, they started their job after 1996. The results are reported in Tables 3.8 and 3.7 in Appendix 3.A. The coefficients of the interaction terms have the same sign as in the benchmark estimation, but are larger in magnitude. The probability that an unemployed person participates in training is estimated to have dropped by 6.6% in the linear probability model and by 6.9% in the probit model. The coefficient in the probit model is now significant only on the five percent level, which is probably due to the reduced size of the treatment group.

3.3 Implications

The estimates from both models indicate that the relaxation of employment protection in 1996 had a negative impact on training on the job. Firms are less likely to train their employees due to the relaxation of employment protection. These results should be seen as tentative because it is difficult to identify those individuals who were eligible to employment protection and those who are not. The results of the empirical exercise corroborate the findings from the simulation in chapter two: a moderate degree of employment protection can provide an additional incentive to organize training for their employees. Politics should take this into account when reforming the employment protection legislation. If the aim is to keep the human capital level on a high level, a reduction of employment protection should be accompanied by the introduction of other instruments that promote on-the-job training.

(2008).

Appendix 3.A

Additional tables

Table 3.7: Estimation Results of Linear Probability Model under Alternative Specification of the Treatment Group

	Coeff.		t-stat	Coeff.		t-stat
Group	-0.015		1.25	-0.014		1.02
1999	0.024	**	5.30	0.027	**	5.87
Interacted				-0.066	**	-3.48
Female	-0.093	**	-17.85	-0.094	**	-18.02
Age	0.011	**	16.92	0.011	**	16.90
Age squared	0.000	**	-19.65	-0.000	**	-19.65
Schooling						
- no degree	0.058	**	4.27	0.058	**	4.27
- low degree	0.155	**	10.76	0.155	**	10.76
- intermediate	0.243	**	13.79	0.243	**	13.79
- high1	0.206	**	12.40	0.206	**	12.40
- high2	0.117	**	5.07	0.117	**	5.07
university	0.030	**	2.75	0.030	**	2.75
blue collar	-0.205	**	-37.63	-0.205	**	-37.63
foreigner	-0.105	**	-10.56	-0.104	**	-10.56
East Germany	0.047	**	7.85	0.048	**	8.07
No. obs	41,025		41,025			
F-Stat	F(58,41)=151.1			F(59, 41) = 148.85		
PCP	71.41			71.37		
R^2	0.153			0.153		

Notes: Results from estimation of a linear probability model. Group is a dummy for workers who have a job tenure of less than tree years and who work in establishments of size 5-9 employees. "1999" is a dummy for observations in that year. The interaction is between these two dummies. Standard errors are calculated using the White-heteroscedasticity robust estimator. Controls included are: size classes (1-4, 5-9, 50-99, 100-499, 500-999, 1000 or more), Age, Age squared, Dummy for female, 39 Industry-dummies, Dummies for different level of schooling: left school without degree, low degree (Hauptschule), intermediate degree (Mittlere Reife), High1 (Fachhochschulreife), High2 (Abitur), Dummy for graduates of university, dummy for blue-collar worker, Dummy for East Germany, Dummy for not-German citizens. PCP is the percentage of outcomes (participation or non-participation) that are correctly predicted by the model. Stars indicate significance on the 5%-level, double stars on the 1%-level.

Table 3.8: Estimation Results of the Probit Model under Alternative Specification of the Treatment Group

	Ave. Marg. Effect		z-Stat	Ave. Marg. Effect		z-Stat
Group	0.019		1.41	-0.057	**	3.22
1999	0.028	**	5.72	0.032	**	6.33
Interaction				-0.069	*	-3.38
Female	-0.102	**	-17.92	-0.102	**	-17.92
Age	0.013	**	16.15	0.013	**	16.16
Age squared	0.000	**	-18.78	0.000	**	-18.79
Schooling						
- no degree	0.142	**	4.35	0.142	**	4.34
- low degree	0.256	**	7.52	0.256	**	7.51
- intermediate	0.352	**	9.44	0.352	**	9.43
- high1	0.313	**	8.55	0.313	**	8.54
- high2	0.232	**	5.48	0.232	**	5.47
university	0.022	*	2.05	0.022	*	2.05
blue collar	-0.220	**	-36.89	-0.220	**	-36.90
foreigner	-0.122	**	- 9.18	-0.122	**	- 9.17
East Germany	0.057	**	8.75	0.057	**	8.80
No. obs.	41,025			41,025		
LR-test	$\chi^2(59)$	=6674.56		$\chi^2(60)$	=6686.00	
PCP	71.42	%		71.46	%	
Pseudo R^2	0.128			0.128		

Notes: Results from Probit regression. Marginal effects reported are those that correspond to an average individual. Variables and controls are the same as in Table 3.7. Stars indicate significance on the 5%-level, double stars on the 1%-level.

Concluding Remarks

This dissertation has examined questions concerning the implications of labor market institutions and allocative outcomes. The first chapter has dealt with the impact of the business cycle on wage setting. Using data from the Current Population Survey I have constructed an aggregate time series for the wage of workers newly hired out of non-employment. I have found that these wages of newly hired workers react one-to-one to productivity fluctuations, whereas wages of workers in ongoing job relationships react very little to changes in productivity. Controlling for cyclical variation in the skill composition of the workforce is important for this result, and I have shown that the average skill level of the workforce is captured well by the average number of years of education. The finding has been related to existing studies on the cyclicality of wages of job changers and it has been shown that wages of new hires out of non-employment behave similarly to wages of job-to-job movers.

This result points against rigidity in the wage of newly hired workers as an explanation for the volatility of unemployment over the business cycle as forwarded by Hall (2005), Gertler and Trigari (2006), and Blanchard and Galí (2008). However, a moderate degree of wage rigidity or alternative calibrations as in Hagedorn and Manovskii (2008) or Hall and Milgrom (2008) are within the confidence interval of the estimates. Finally, the baseline estimates are based on the post 1984 period. Evidence indicates that wages of newly hired workers were more rigid prior to that year.

In the second chapter I have developed a model that combines matching in the labor market with human capital formation in the workers' life cycles. In this setting I have introduced employment protection and analyzed the consequences on the firms' incentives to invest in the training of their employees. The simulation has shown that a moderate level of a firing tax increases investment in human capital, but a large firing tax is detrimental to vacancy creation and training. Workers benefit from a moderate firing tax in two ways: They get more training when they are young, and they benefit from secure employment when they are old. The positive effect of a firing tax on training arises because firms avoid payment of the firing tax by keeping the worker instead of laying her off. However, when the firing tax is too high, these positive effects cannot be observed. A mandated severance payment does not have these beneficial effects because it leads to a rise in the wage of the same size. This is due to the assumed wage setting mechanism, where the wage is determined by Nash-bargaining and the severance payment increases a worker's outside option. Therefore, it has no effect on the layoff decision, nor does it increase the firms' incentives to invest in the workers' human capital. Both policy instruments reduce profits and vacancy creation, young workers face more difficulties to find a job.

In the third chapter I have examined the interaction of employment and training on the job from an empirical perspective. I have found that the reduction of employment protection in 1996 led to a reduction of training on the job. I have found that a worker's probability to participate in training was reduced by 3%. Firms are less likely to train their employees due to the relaxation of employment protection. However, these results should be seen as tentative because it is difficult to identify those individuals who were eligible to employment protection and those who are not. This result corroborates the findings from the simulation in chapter two: a moderate degree of employment protection can provide an additional incentive to organize training for their employees.

The findings imply that a reform of labor market institutions that reduces employment protection should be accompanied by policies that encourage investment in the workers' human capital.

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